Essays on Asset Pricing

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Declaration of Originality

I hereby declare that this dissertation is composed of my original work, and contains no material which has been previously published in a thesis, dissertation submitted for a degree or diploma by the University or any other institution. I alone remain responsible for the content of the following, including any errors or omissions which may unwittingly remain.

Biplob Chowdhury

Hobart, Tasmania

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Preface

The essays in this dissertation represent collaborative efforts with my supervisors. Chapters 2, 3 and 4 are based on joint work with Professor Mardi Dungey and Dr. Nagaratnam Jeyasreedharan.

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Dedication

To all the freedom fighters involved in the Bangladesh Liberation War of **1971**, for their struggles and sacrifices to give birth to our beloved motherland, **Bangladesh.**

Abstract

Significant jumps have been found in stock prices and stock indexes, suggesting that jump risk is a part of systematic risks. Since jump risk is priced, adding jump risk into the traditional finance models has significant empirical and theoretical meanings. This dissertation focuses on testing and exploring the usage of the jump-diffusion two-beta asset pricing model.

The dissertation consists of three essays: The three essays, investigate the dual beta (i.e. diffusion beta and jump beta) asset pricing model conditional on the state (i.e. up or down) of the market, the quantile relationships between standard beta, diffusion beta and jump beta and lastly, the quantile relationships between beta-changes and volume.

The first essay of this dissertation concerns the capital asset pricing model (CAPM) beta (or standard beta), which is assumed to be the sole and constant measure of systematic risk in the CAPM model. However, it is now considered an empirical fact that the beta of a risky asset or portfolio is not the sole measure of systematic risk but is also time varying. Often, the market beta is not enough to explain the cross-sectional variations of average equity returns. For this reason researchers have proposed alternatives to the classical CAPM. More specifically, Todorov and Bollerslev (2010) showed that the CAPM beta can be further decomposed into a diffusion beta and a jump beta. Therefore, the first essay of this dissertation investigates whether assets with different decomposed betas are priced more efficiently. In particular, we investigate the systematic risk exposures of Japanese banks for both continuous and discontinuous market risks.

Using high frequency data from 2001 to 2012, we decompose the standard betas of Japanese banking stocks into its diffusion and jump components. We find that jump betas on average are larger than diffusion betas, indicating that stocks respond differently to information associated with continuous and discontinuous market movements. We also find that larger stocks are more sensitive to discontinuities than their smaller counterparts; high leveraged stocks are more exposed to unexpected market-wide news and profitable firms are equally sensitive to both

diffusion and jump market risks. By allowing for asymmetric market states we show that diffusion and jump betas both carry large and significant premiums in both up and down markets, but that these premiums differ substantially during periods of financial crises from those present during stable conditions.

The second essay also applies the CAPM decomposition approach to compute the diffusion betas and jump betas. However, this essay takes a step further from the second essay and estimates the quantile-relationship(s) between standard betas, diffusion betas and jump betas of individual stocks and portfolios in the Japanese market. It also examines whether the beta in the standard CAPM is the weighted average of the jump beta and diffusion beta in the decomposed (jump-diffusion) CAPM model. A key insight of this essay is that even though the diffusion returns and jump returns are orthogonal according to the Todorov and Bollerslev (2010) decomposition, the two component betas (i.e. diffusion and jump betas) are neither restricted nor found to be orthogonal. Using quantile regression techniques, we find that jump betas have a higher variability than the diffusion and standard betas and the relationship(s) between the three betas are non-linear. Our findings also demonstrate that standard beta is more weighted by diffusion beta than jump beta, although the actual magnitudes of the weights differ significantly across the quantiles. We also show that the betas vary systematically across (large and small) firm sizes. Empirically, we also find support for the notion that the standard CAPM beta is a 'summary proxy' for the systematic risks in a jump-diffusion market process, i.e. a weighted average of the diffusion beta and the jump beta (at the median quantile).

The third essay applies the same quantile-regression methodology, as used in the third essay, to examine the behaviour of time-vary beta-changes (or beta uncertainty) conditional on trading volume. By quantile-regressing the various betas (standard beta, diffusion and jump beta) on trading volume, our results depict a non-linear relationship. The volume-beta relationships at the tail quantiles are found to be quite different from those at high quantiles and at the mean. Since the systematic risk, beta, is a function of price-changes (price uncertainty) (according to the CAPM), we also examine whether the observed non-linear linkages between beta and volume is also analogously mirrored by price-changes and volume**.** The findings indicate a positive (negative) relationship between stock price changes and volume from top (bottom) quantiles. The relation is not entirely contemporaneous since lagged volume also found to contain predictive power for price-changes.

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Chapter 1

Introduction

Over the last few decades, global financial markets have experienced major structural changes and severe crisis periods. The financial crisis of the late 1990s, and the very recent global crisis of 2007–2008, resulted in enormous costs to many countries, with devastating effects on the global economy. Triggered by a real estate bubble, overly leveraged financial products, and failures of AIG, Lehman, Merrill, and other major financial firms, the "Great Recession" of 2008–09 saw America's GDP contract by more than 4 per cent and that of some countries by double digits. This has led to a questioning by the community of the credibility of our current understanding in finance and financial behaviour. These crises have led to a further growing awareness of the need for appropriate risk management techniques and structures within organizations. In this dissertation, we seek to understand the driving factors of firm's risk exposure by considering how the market affects asset prices. That is, how an individual firm's equity prices respond to continuous and discrete market moves and how these different market price risks, or betas, are priced, as well as, how these different betas behave across different firms.

A firm's risk is defined as the risk inherent in firm's operations as a result of external or internal factors that can affect a firm's profitability. Firm risk is typically divided into two parts: idiosyncratic risk (firm-specific risk) and systematic risk which results from exposure overall market shocks and is often represented as market risk. The portfolio theory of Markowitz (1952) decomposes an asset risk into the diversifiable and non-diversifiable risk. Since an asset diversifiable risk can be completely removed through the diversification, the price-related risk of an asset is non-diversifiable risk. Based on these Sharpe (1964) and Lintner (1965) developed the capital asset pricing model (CAPM). Since an asset's diversifiable risk can be completely cancelled out, CAPM says a theoretically appropriate expected return of an asset depends on the asset's non-diversifiable risk, not its whole risk. As a result, the risk premium on an asset is determined by its systematic risk. This thesis examines the relationship between systematic risk and stock returns in the financial industry with a focus on banking stocks.

Cross-sectional asset-pricing studies typically exclude financial institutions because of their high leverage and the high level of industry regulations. This suggests that financial firms may be suspected to be outliers in any study spanning industries with differences in capitalization and regulation. For example,Fama and French (1992, 1993) exclude financial firms in their study. They state ''. . .we did not include financial firms because the high leverage that is normal for these firms probably does not have the same meaning as for nonfinancial firms, where high leverage more likely indicates financial distress. . .'' (Fama and French, 1992, pp. 429). Most of the numerous studies that extended the Fama French model have followed their approach and excluded financial firms.[1] The fact that the model excludes financial firms is problematic because financial firms make up a substantial fraction of the domestic equity market. Moreover, the exclusion of financial firms can be questioned on both theoretical and empirical grounds. The theoretical structure originally developed by Modigliani and Miller (1958, 1963) demonstrates that leverage can change the risk profile (beta) of a firm but it does not invalidate the central principles of the CAPM. In this sense, it would be more desirable if the pricing model is generally applied rather than restricted to nonfinancial corporations.

We concentrate on financial firms to examine firms' reactions to different forms of market movements. The recent financial and sovereign debt crisis highlights the multi-dimensionality of financial firms' risk exposures. This thesis focuses on the banking sector as the global banking markets were hit hard by the crisis. Although there exists an extensive literature on common risk factors in stock returns (Goyal 2012), most research is devoted to industrial firms, for example by focusing the single factor CAPM and its extensions.

Empirical evidence for bank risk remains rather scarce, because empirical studies usually exclude banks based on their inherent difference from industrial firms (Gandhi and Lustig 2015). Banks are different from non-financial firms in many ways. One of the most salient distinctions is that banks are subject to bank runs during banking panics and crises, not only by depositors, but also other creditors (Gorton 1988, Gorton and Metrick 2012, Duffie 2010). Banks also differ from industrials with respect to their business activities, leverage, regulation,

[1] Some exceptions are Baek and Bilson (2015), Baele et al. (2015), Viale et al. (2009), and Bessler et al. (2015) among others.

and systemic importance. Moreover, in financial crisis periods there is a threat of bank runs, with the potential to increase the probability of bank failures leading to systemic risk. Therefore, understanding the sources of banks' risk exposures is essential for bank regulators, investors, and bank customers. In this dissertation, we investigate the time-varying systematic risk exposures of banks in order to better understand the sources and the relative pricing of risk by taking advantage of this special nature of banks as compared to regular industrial firms. It is important for banks to understand the determinants of equity risk premise, since this premium not only affects their investment decision but also their financing decision. As is well known, the weighted average cost of capital (WACC) is a weighted average of the costs of debt and equity. The higher the equity risk premium, the higher the required rate of return on equity, and thus, the higher the WACC. The variation of risk premium is also of interest to regulators because it contains information about market perception of bank risk. Thus, if banks have increased their exposures to certain risks, regulators should consider actions, such as additional loss provisioning, additional capital infusion, as well as revising the required deposit insurance premium paid. Thus, this paper contributes to the asset-pricing literature by providing empirical evidence on the systematic risk factors that are relevant in pricing bank equities.

According to Sharpe (1964) and Lintner (1965) CAPM, the systematic component of risk, measured by beta, should be priced. Although numerous studies over the past half-century have challenged the ability of CAPM to explain the cross-section of expected stock returns, it still remains the workhorse of finance for estimating the cost of capital and capital budgeting for firms. Meanwhile, more recent empirical evidence pertaining to the equity risk premium and the pricing of risk at the aggregate market level suggests that the expected returns variation associated with discontinuous moves, or jumps, is priced higher than the expected continuous price variation.[2]

Although there is no consensus on what constitutes a jump and what distribution it follows, evidence generally supports the hypothesis that jumps exist in asset prices. Jumps are infrequent but abnormal changes in stock prices, often driven by significant information shocks or liquidity shocks. Early empirical evidence of jumps in stock prices and option pricing model was provided by Press (1967) and Merton (1976). Subsequent studies such as Ball and Torous (1983), Jarrow and Rosenfeld (1984), Akgiray and Booth (1986) and recent studies from

[2] See, Pan (2002), Eraker et al. (2003), Bollerslev and Todorov (2011), among others

Barndorff-Nielsen and Shephard (2004), Andersen et al. (2007),Lee (2012), amongst others provide convincing support for jumps in stock prices and other assets.

The option pricing literature generated early interest concerning jumps and their consequences for asset pricing, starting with the classical papers by Cox and Ross (1976) and Merton (1976). They examine the effects of jumps on option pricing beyond the classical diffusion model of Black and Scholes (1973). While the classical Black-Scholes diffusion model can generate heavy tails in returns, it cannot generate sudden, discontinuous moves in prices. The valuation of options becomes more difficult when prices follow processes that include jumps because it will no longer be possible to form a risk-free portfolio, as in Black-Scholes approach to option pricing, Cox and Ross (1976) and Merton (1976) extend the Black-Scholes diffusion to include a jumps representation of the price process. However, their model assume that jumps are idiosyncratic risk, i.e. the prices of underlying asset are uncorrelated with price changes in the market, and therefore jump risk is not priced. Subsequent studies such as, Naik and Lee (1990), Bates (2000), Pan (2002), Eraker (2004) and Yan (2011) demonstrate that incorporating jumps contributes to explaining observed option prices. Strong empirical evidence from the effects of jumps motivates our research in this dissertation.

In a jump-diffusion process, the stock price process is characterized by a diffusion Brownian motion component plus a pure jump component. The diffusion part is the usual flow of news that gives rise to frequent and relatively small price changes i.e. the change in stock prices may be due to the variation in capitalization rates, a temporary imbalance between supply and demand, or the receipt of any information which only marginally affects stock prices, while the jump part is a rarer event, such as release of important information, a liquidity shock, regional or global financial crisis or even serious terrorist attack to major industrial country with strong economic power in the world, that causes an abnormal changes in price of stock. Naik and Lee (1990) study a general equilibrium model, which includes premia for both jumps and diffusion risks in order to price European options on the market portfolio. Their model states that option traders price the expected variation in equity returns associated with large price discontinuities or jumps, differently from the expected variation associated with smooth or diffusion price moves. When commenting on Merton's (1976) model, they point out that a "feature of Merton model is the assumption that the jumps in security prices are uncorrelated with return on the market portfolio. Clearly, this assumption is violated if the security under consideration is the market portfolio itself (p.495)". An important contribution of the ability of the Naik and Lee's equilibrium model is to explain the jump risk as systematic risk, an aspect omitted by Merton (1976).

If jump risk is priced in an option, one would expect it will be priced in the underlying stock returns themselves, and if the return of stocks should be divided into a jump part and diffusion part certainly the risk associated with stock returns should be decomposed into two parts also. Decomposing risk into diffusive risk and jump risk components may offer a new perspective and answers to the following questions,

(I) How might diffusive risk and jump risk be measured?

(II) Are there differences in sensitivities to two types of systematic risk? The possibility of identifying and quantifying jump risk also raises interesting questions concerning investors' remuneration for bearing risks.

(III) Is there a premium for jump and diffusive risk?

(IV) And what are the levels of risk premia for these factors during normal market conditions and when markets are in turbulence?

To address those questions, we adopt a continuous-time capital asset pricing model framework where it is assumed that asset prices follow a correlated jump-diffusion process. In the classical capital asset pricing model (CAPM), systematic risk, measured by beta, is determined by the asset's covariance with the market over the market variance.[3]

The CAPM assumes that security returns are generated by a continuous process. Return distributions, however, are more leptokurtic than the normal one as noted by Fama as early as 1965. Hence, recent studies on the stochastic behaviour of the stock market generally agree that stock returns are generated by a mixed process with a diffusion component and a jump component. In this sense, the CAPM beta may only capture a part of a mixed process, and the standard CAPM beta is at best a 'summary proxy' for the systematic risk of a mixed-process, i.e. a weighted average of the diffusion component and the jump component. Therefore the beta of the CAPM is not an accurate risk measure when the price process has jumps. If so, it would be prudent to be able to split the standard beta into two component betas so as to capture the two risks separately: one component for continuous and small changes (diffusion beta) and

[3] The CAPM has seen numerous extensions, such as conditional asset pricing factors such as, size, value, and momentum (Fama and French (1993), Jegadeesh and Titman (1993), and Carhart (1997)); liquidity (Amihud (2002), Pastor and Stambaugh (2003), and Acharya and Pedersen (2005)); preference-based factors such as the downside betas of Ang et al. (2006) and the co-skewness of Friend and Westerfield (1980) and Harvey and Siddique (2000); and factors relating to deviation from market equilibria, see Lettau and Ludvigson (2001).

the other for discrete and large changes (jump beta). These two types of risk are different in nature and require different treatments. They should be differently priced, hedged and managed. Consequently, being able to estimate them separately has implications for financial services, and hence the wider economy. The core of this dissertation is to examine the financial market behaviour in the presence of jumps and to analyse the effect of two different sources of uncertainty in a jump-diffusion economy using a general CAPM framework.

The first essay of this dissertation, beginning in Chapter 2, examines the behaviour of diffusive and jump systematic risk for the Japanese banking sector and how investors price these two systematic risks under different market conditions. The particular interest in studying the Japanese market is driven by its specific financial and governance system (relationship-based) and there are only few empirical studies of the Japanese market. The contribution of our study is to add to the existing literature based essentially on US market empirical and theoretical results are less studied countries, in particularly, the Japanese market. Also, the Japanese banking sector is strongly developed, but with a distinctly different character from that of most Western economies, including particularly strong direct linkages between the banks and companies in the real economy – strong enough for a particular form of 'wealth' contagion to emerge between the financial markets and real economy through the complex web of accounting interactions, as shown in Kiyotaki and Moore (2002). CAPM estimates for the banking sector are relatively rare, and recent estimates for Japan are rarer still; King (2009) provides empirical estimates for banking sectors across a range of countries, and demonstrates the differences in Japan where relatively high beta have been maintained for over two decades, while a group of papers provide evidence for samples prior to the 21st century; Elyasiani and Mansur (2003), Gultekin et al. (1989), and Andersen et al. (2000) characterize volatility in the Japanese stock market based on a short sample of high frequency 5 min Nikkei 225 index return. To our knowledge there is no study of CAPM on Japan which takes account of recent advances in high frequency financial econometrics although Bollerslev and Zhang (2003), Andersen et al. (2006), Todorov and Bollerslev (2010), all provide evidence that using high frequency data improves estimation of beta over traditional regression based procedures using lower frequency data.

Chapter 2 uses recent developments in high frequency financial econometrics by Todorov and Bollerslev (2010) to estimate beta for the Japanese banking sector using high frequency intra-day data. The unique aspect of this approach is to decompose the systematic risk into a continuous and discontinuous component, following the asset pricing literature which suggests the evolution of prices follows a continuous process such as Brownian motion augmented with discrete jump events. The expected stock return is dependent on both sources of risk. The diffusive component of the return is determined by the covariance between the diffusion process driving the market return and the stock processes, a well-known continuous-time analogue of the discrete time β-representation. The jump component of the return is captured by the covariance between the jump-distributions of the market return and stock processes. We decompose standard CAPM beta into diffusion beta, attributable to general market volatility and jump beta associated with sudden disruption in the price process due to arrival of new information in the market. We aim to explain how individual stocks are influenced by systematic diffusive risk and jumps risk and we find that jump beta exceed the diffusion beta. Patton and Verardo (2012) provide an excellent motivation for why these beta may differ, arguing that information sufficient to cause disruption may attract greater market reaction speeds than the normal process. In addition to beta relationships, Bollerslev et al. (2015) have found the risk premiums associated with jump beta is statistically significant, while the diffusion beta does not appear to be priced in the cross-section. In another independent study on asset pricing Pettengill et al. (1995) showed that market premiums differ between up-markets and down-markets. These multiple insights lead one to expect not only an analogous dual beta behaviour over the entire sample periods but also risk-premium differences between up-markets and down-markets.

We introduce and test a new 4-beta CAPM model by combining the diffusion and jump betas of Bollerslev et al. (2015) and the conditional betas of Pettengill et al. (1995) into a single model to detect any significant differences under differing market conditions. Therefore, our model includes upside market diffusion, upside market jump, downside market diffusion, and downside market jump components. Because of this decomposition, the model in this chapter is sufficiently general to accommodate the research purpose of revealing how different factors are priced. Another feature of the model is that it explicitly allows individual stock prices to respond to the separated market components with different magnitudes. Accordingly, we can estimate the various exposures of a stock price to different risk factors and the associated risk premiums and specifically identify the most important systematic risk components that explain stock returns.

Our jump-diffusion two-beta asset pricing model provides an alternative to the CAPM. It prices both jump and diffusion risks. The empirical tests of this dissertation chapter show that it is a better asset pricing model than the CAPM, particularly for the period when jumps are included in the price process. In a resulting modified CAPM expected returns are still linear in beta, but additional premia are required to compensate the investor for taking on jump risk.

The jump-diffusion asset pricing model has two different types of beta. It is two dimensional instead; where one dimension measures the systematic risk when no jump occurs, and the other measures the systematic risk when jumps occurs. These two types of beta are independent by definition. Although the two-way decomposition beta allows us to ask how individual equity prices respond to diffusion and jump market moves, it does not allow us to differentiate the jump-diffusion model from the conventional CAPM.

In Chapter 3, we test whether the jump-diffusion model is related to the CAPM. The key insight in this chapter is that, although the diffusion returns and jump returns are orthogonal by the Todorov and Bollerslev (2010) decomposition, the three realised betas (i.e. standard, diffusion and jump betas) are not restricted nor expected to be orthogonal. In fact, a simple correlation test indicates some dependencies. We explain the relationship between standard beta, diffusion beta and jump beta across different banks and how these different betas behave across different banks. We empirically show that jump-diffusion model is related to the CAPM, i.e. the systematic risk is equal to the weighted average of diffusion risk and jump risk. We find that on average the standard beta is weighted more by the diffusion beta component then the jump beta component. The relationship holds across the quintiles. However, the actual magnitude of the weights differ across the quintiles. In general, the weights are jointly lower for low standard betas until the pick around the 50^{th}-75^{th} quintiles with value dropping down again post 75^{th} quantile. Further, when jump risk is diversifiable in the market portfolio the model is reduced to the standard CAPM.

Prior empirical studies of the CAPM assume that a stock's beta is constant through time, while our jump-robust version of the CAPM finds significant evidence of variation in betas at monthly frequencies. The variation in a stock's beta may be due to the influence of either micro factors such as operational changes in the company, or changes in the business environment peculiar to the company, and/ or macro factors such as the rate of inflation, general business conditions and expectations about relevant future events.[4] However, the literature suggests that the variation in the stock's beta due to the influence of macroeconomic factors is limited. Therefore, in chapter 4, we further investigate the time variation in betas by adopting a microeconomic, rather than macroeconomic view on factors. Particularly, we investigate whether changes in time-varying betas can be explained by trading volume. Trading volume, in addition to price, represents an important source of information in stock markets. As with information about prices, information about volumes is publicly available. We hypothesize that trading volume can explain time-variation in CAPM beta changes, stemming from market microstructure models, such as the well-known mixture of distribution hypothesis (MDH) of Clark (1973), which assumes that trading volume is a proxy for speed of information flow to the market. The MDH implies a positive relationship between trading volume and price variability, and this relationship is a function of a mixing variable defined as the rate of information flow. Blume et al. (1994) show that trading volume provides information about the quality of information signals rather than the information signal itself. This motivates us to use trading volume as a potential explanatory variable for the time variation betas.

Since the systematic risk, beta is a function of price-changes (according to the CAPM), we also examine whether observed linkages between beta and volume is also analogously mirrored by the price and volume relationship. Therefore, in the last section of chapter four, we further investigate the nature of volume-return relation. We establish a dynamic and significant linkage between beta changes and volume as well price changes and a volume-return relation relationship, assigning a special importance to trading volume as a proxy for the rate of information flow to the market.

Finally, Chapter five summarises the implications of the research findings of this study, presents its limitations and outlines potential avenues for further research.

[4] See, Sharpe et al. (1974), Bos and Newbold (1984), Ferson et al. (1987), Shanken (1990), Ferson and Schadt (1996), Lettau and Ludvigson (2001), Andersen et al. (2005), Lewellen and Nagel (2006), Mergner and Bulla (2008), among others.

Chapter 2

An Empirical Examination of Jump Risk in Asset Pricing: Evidence from Japan

2.1. Introduction

The Japanese banking sector is an important source of global international capital. Although not at the levels at which it previously dominated international cross-border banking in the 1990s, since 2011 Japanese banks have re-emerged as the largest supplier of international bank credit; see Rixtel and Gasperini (2013). This change appears to be at least partly due to the historically conservative lending practices of Japanese banks, which have proven attractive in the more risk conscious post-2008 environment; see Batten and Szilagyi (2011). The role of Japanese banks in the global financial system makes them of significant importance to investors and international regulators, with three Japanese institutions identified as globally systemically important banks (G-SIBs) by the Financial Stability Board (2013 -2015) and existing evidence of global transmission of shocks through the banking sector; for example Elyasiani and Mansur (2003), Van Rijckeghem and Weder (2001, 2003), and Dungey and Gajurel (2015).

The prominence of banks in the Japanese economy and the frequent association of the health of the banking sector to the whole economy suggest that understanding of the sources of bank risk exposure is essential for bank regulators, investors, and bank customers; individual bank failures may result in contagion effects and systemic risk. Financial market crashes, such as experienced in 2008 and the European debt crisis of 2010 to 2012, demonstrably impact the performance of the real economy, and an important avenue of transmission between the sectors is via banking relationships. Our developing understanding of how markets absorb news links information assimilation to discontinuities in asset prices; see Patton and Verardo (2012).

Our point of departure is the familiar capital asset pricing model (CAPM), which allows a simple decomposition of total variation of returns (a standard measure of risk) into a common, systematic portion and a firm-specific, idiosyncratic component. We expand this single-factor framework to include a range of additional risk factors, the jump systematic risk and diffusion systematic risk factors, and then compare significance, explanatory power, stability, and impact on the systematic decomposition across the models. Accurately disentangling systematic and idiosyncratic factors is critical from a variety of perspectives. Correlation of risks has implications for the stability of the financial sector and the macroeconomy via systemic risk concerns, and this necessarily reflects systematic factors because idiosyncratic risk, by definition, is (or ought to be) cross-sectionally independent.

Identifying the systematic risk factors among financial firms is important both in understanding the pricing of equities generally and for public policy purposes. Financial firms make up a substantial fraction of the domestic equity market. Indeed, they have comprised almost 15% of the market value of all firms listed on Tokyo Stock Exchange (TSE) in recent years, and their stock returns have been found to have a significant relationship with future economic growth (see Cole et al. (2008)). Moreover, extensive deregulation of financial and banking firms' asset and liability powers in the 1980s and 1990s increased the importance of regulatory control over the risk-taking behavior of these firms. Following years of discussion over how best to modify Basel I capital requirements, the recently adopted Basel III standards increasingly emphasize the use of market discipline as a major regulatory device. However, using market factors to evaluate and control risk-taking behavior of banks by either private market forces or public regulators requires an understanding of the risk factors that are priced in security markets for these firms. This study fills a gap in the existing literature by providing empirical evidence on the systematic risk factors that are relevant in pricing bank equities using available data for Japanese banks.

Japan presents a particularly interesting case study for several reasons. First, Japan is one of the largest advanced economies in the world and a model for many East and South East Asian nations' development ambitions. Second, the Japanese banking sector is very different from US banking sector, and plays a crucial role in the Japanese economy. Banks hold a large share of the country's finances and bank deposits constitute almost half of household assets (Uchida and Udell 2014). For much of the post-war period, banks were the major source of external financing for Japanese firms and the country became a bank-centered financial system (Yamori et al. 2013). Japanese banks have built a strong customer base and have cultivated close ties with their client firms. Thus, the importance of banks in the Japanese economy and the close connection of bank sector health suggest that the systematic risk of Japanese banks may differ from those in other jurisdictions[5]. Finally, the Japanese capital market is unique because the institutional setup of the Tokyo Stock Exchange (TSE) is significantly different from the commonly analyzed US equity exchange, including lunch breaks, with a batched trading process, *Itayose*, used to clear orders at the start of each trading session, followed by a continuous auction. *Zaraba* for the rest of the session. The actual trading on the exchange is done by specialized security houses, -- *Saitori* members -- who are responsible for matching the orders without taking positions themselves. For more details, see, Amihud and Mendelson (1991), Lehmann and Modest (1994), Hamao and Hasbrouck (1995), and Andersen et al. (2000).

In this chapter, we examine unexpected changes, known as jumps, in Japanese bank stock prices. The ubiquity of jumps has important implications for investors who rely on portfolio diversification for risk control. If jumps are idiosyncratic to individual companies, they might be a second-order concern. But if jumps are broadly systematic, portfolio diversification may not be an effective jump-risk mitigating strategy. Recent empirical studies find that jumps have distinctly different implications for risk measurement and management, portfolio allocation, and derivatives pricing and hedging. However, hedging effectiveness may be hindered by systematic jump risk. The recent credit crisis attests the significance of such risk and undiversifiable systematic jump risk amplifies its economic significance (Jarrow and Rosenfeld 1984). Das and Uppal (2004) find that returns on international equities are characterized by jumps and these jumps tends to occur at the same time across countries leading to systemic risk. The systemic jump risk has two effects: it reduces the gains from diversification and it penalizes investors for holding leveraged position. Kim et al. (1994) find that Poisson distributed jumps,

[5] The Japanese banking system consists of national banks ("city banks"), regional banks, trust banks, long-term credit banks, as well as credit cooperatives, foreign banks and postal savings bank. The segmentation is historically related to bank-firm relationships, so that larger banks provided loans to larger, and (presumably), more reputable and transparent companies(Uchida et al. 2008). Moreover, the segmentation was enforced by the government for ease of regulation, so the ban on consolidation across commercial banking, trust banking, long-term credit banking, securities and insurance was abolished only by the 1997 revision of the Antimonopoly Law (Harada and Ito 2011). While competition on deposit markets is not constrained by bank category, lending may still be segmented despite bank deregulation: large banks have entered the market for loans to small and medium-sized enterprises (SMEs), but still take second place in this business compared with regional/second-tier banks (Uchida et al. 2008). The distinct roles of banks in each bank charter in Japan is similar to the industry equilibrium in the U.S., where larger and smaller banks focus on different types of business, obeying the predictions of economic theory on the comparative advantages of large and small institutions (DeYoung 2014).

observed from both the index and its component stocks are non-diversifiable risk, implying that the standard assumption in asset pricing that these jumps are not priced may be invalid.

A large body of literature has evolved to show both theoretically and empirically that jumps explain many of the dynamic features of stylized facts documented in asset prices. The presence of jump variations in both individual assets and the aggregate market will affect co-volatility estimation and consequently the measurement of realized beta and systematic risk. The possibility of identifying and quantifying jumps rises a lot of interesting questions concerning investors' remuneration for bearing risks. Is there a premium for the jump risk? What kind of jumps do/ should bear a risk premium? Is there a risk premium for systemic jumps? In this chapter, we shed light on the behaviour of jump systematic risks for the banking sector and how they are priced.

To address these questions we use a continuous-time Capital Asset Pricing Model (CAPM) where it is assumed that asset prices follow a jump-diffusion process. CAPM estimates for the banking sector are relatively rare, and recent estimates for Japan are rarer still; King (2009) provides empirical estimates for banking sectors across a range of countries, and demonstrates the differences in Japan where relatively high beta have been maintained for over two decades, while a group of papers provide evidence for samples prior to the 21st century; Elyasiani and Mansur (2003), Gultekin et al. (1989), and Andersen et al. (2000) characterize volatility in the Japanese stock market based on a short sample of high frequency 5 min Nikkei 225 index returns. To our knowledge there is no study of CAPM for Japan which takes account of recent advances in high frequency financial econometrics although Bollerslev and Zhang (2003), Andersen et al. (2006), Todorov and Bollerslev (2010), all evidence that using high frequency data improves estimation of beta over traditional regression based procedures using lower frequency data.

Given this background, this chapter uses recent advances in financial econometrics to separate beta into jump beta and diffusion beta in the Japanese banking sector. Jump beta represents the impact of market price disruptions on the firm, while diffusion beta represents the response to the evolution of the underlying price process. The motivation for this separation comes from a learning argument akin to the one put forward in Patton and Verardo (2012) regarding short-term changes in beta in response to firm earning announcements. They hypothesize that beta may temporarily increase around earnings announcements as the market pays attention to the announcements in order to absorb any new information the announcements may contain and convey. Combining this argument with the known association of jumps with the arrival of unanticipated news,[6] we expect that jump beta magnitudes to exceed diffusion beta magnitudes.

We implement the approach of Todorov and Bollerslev (2010) to estimate jump and diffusion beta for 50 Japanese banking stocks for the period from January 2001 to December 2012. We estimate the two separate betas as well as a standard CAPM regression-based beta for each of the individual stocks using high frequency 5-minute intra-day data on a non-overlapping monthly basis. Estimates for diffusion, Jump and standard betas are computed on a month-by-month basis. High frequency data permits the use of 1-month non-overlapping windows to analyse the dynamics of our systematic risk estimates. As expected, the jump beta exceed the diffusion beta for almost all banks in almost all time periods, consistent with the small existing literature for firms in the US in Alexeev et al. (2017), Bollerslev et al. (2015), Todorov and Bollerslev (2010) and Indian banks in Sayeed et al. (2017) and the analysis of Neumann et al. (2016) that jumps play an important role in determining risk premia for the S&P500.

We characterize the behaviour of the price series for selected Japanese banks using the Barndorff-Nielsen and Shephard (2006) jump detection test to establish evidence for the existence of jumps. We find 272 jump days out of 2866 trading days, corresponding to 115 jump months out of 144 months, where jumps are detected in the market. We find that on average the jump betas are usually 40% higher than the diffusion betas. These estimates suggest that when news is sufficient to disrupt prices, that is to cause a jump, the speed with which news is disseminated into the market is likely to be even faster than previously estimated using the combined diffusion and jump price process as in Patton and Verardo (2012). This is important for risk managers: if an asset behaves differently during a severe market downturn than it does at other times, this information offers the potential to significantly improve calculations such as Value at Risk (VAR). Moreover, if assets are combined in well-diversified portfolio, then an asset's systematic jump risk is more relevant than the asset's total jump risk. This highlights the importance of decomposing systematic rick into its diffusion and jump components.

[6] See for example, Chatrath et al. (2014), Dungey and Hvozdyk (2012), Lahaye et al. (2011), Evans (2011), Dungey et al. (2009) and Andersen et al. (2007).

CAPM says little about how the riskiness of stocks is determined by firm fundamentals. Corporate finance research suggests that firms' systematic risk is a function of firm fundamentals (e.g. Hamada (1972), Mandelker and Rhee (1984), Ang et al. (1985), Amit and Livnat (1988), Hong and Sarkar (2007)). Therefore, we consider the relationship between different betas and firm characteristics and find that bank size, profitability, leverage, affect both jump and diffusion beta, while capital ratios additionally affect diffusion beta. The empirical findings show that a significant portion of the variation in betas can be explained by the firm fundamentals.

Motivated by these empirical findings we now ask, how market diffusive and jump risks are priced differently under different market conditions. Using a return decomposition method originally proposed by Todorov and Bollerslev (2010), Bollerslev et al. (2015) find that the jump betas carry significant risk premiums. In another independent study on conditional asset pricing Pettengill et al. (1995) show that market risk premia differ between up-markets and down-markets. In this current paper, we introduce a new 4-beta CAPM to enhance our understanding of the cross-section of expected returns. The main empirical contribution of this chapter is to allow the state of the market to have an effect on the risk-return tradeoff. The motivation for this extension lies in the investor's asymmetric preferences between up-markets and down-markets. Investors care differently about downside losses as opposed to upside gain and demand additional compensation for holding stocks with high sensitivities to downside market movements. To test this conjecture, we introduce and test a new 4-beta CAPM model by combining the diffusion and jump betas of Todorov and Bollerslev (2010) and the conditional betas of Pettengill et al. (1995), into a single model to detect any significant differences under differing market conditions. In the context of portfolio of assets, we investigate whether down market risk is priced higher than up market risk. In particular, we carryout significance tests for the price difference between diffusion and jump risks in different market states. This has practical implications for pricing of diffusion and jump risks and can have a direct impact on investor's decision making. It could also shed some light on how investors react to various types of uncertainty. Bearing non-diversifiable jump risk is significantly rewarded, as is evident from the expensiveness of short maturity options written on the market index with strikes that are far from its current level; see Christoffersen et al. (2015) and Driessen and Maenhout (2013) for effects jump risk on options.

We find evidence of significant, and differing, relationships between each of the two measures of beta and stock returns. The estimated risk premia of the up and down markets are not significantly different from the corresponding negative risk premia. The estimated risk premia for both the diffusion and the jump risks for the two market states are found to be symmetric. However, interestingly, we observe that the estimated risk premia for diffusion risk and jump risk are not symmetric during the crisis and post-crisis period. The results imply that investors in the Japanese market respond differently to diffusion risk and jump risk in the periods of up and down markets associated with different degrees of financial stress. Further, we find that large banks tend to have relatively high jump betas. Hence these firms deliver higher returns. Our finding that these relationships differ for jump risk and diffusion risk components aligns with existing literature suggesting the need for a different risk premia for each component (Eraker et al. 2003; Yan 2011; Pan 2002). Consistent with Bollerslev et al. (2015), we find evidence for a positive risk-return relationship, as jump beta is associated with higher returns on average than diffusion beta, consistent with evidence for bank equities in the US in Schuermann and Stiroh (2006) and Viale et al. (2009).

The remainder of this chapter is structured as follows. Section 2.2 discusses the methodological framework. We discuss our sample description in section 2.3. Section 2.4 presents the empirical results. Section 2.5 discusses the results the results from the firm level determinates of betas. Section 2.6 presents our main results on the pricing of jump and diffusion risk in the cross-section of stock returns. Section 2.7 concludes the chapter.

2.2. Jump-diffusions and asset pricing

The estimation framework for distinguishing jump and diffusion betas in individual asset prices consists of two parts. First, a univariate jump detection test is applied to determine days where jumps occur.[7] This selects the days to be considered in the second stage which uses ratio statistics to determine the estimates of the two betas for each stock. We follow the process of Todorov and Bollerslev (2010) and apply the Barndorff-Nielsen and Shephard (2006) jumps test in the first stage as outlined below.

[7] There is no need to test for a jump in the individual stock price, as the estimates of the diffusion and jump betas depend only on whether the factor was diffusion or experienced a jump. We focus explicitly on systematic jump risk, as measured by the exposure to non-diversifiable market-wide jumps and the jump beta since the seminal paper by Merton (1976) hypothesizes that jump risks for individual stocks are likely to be non-systematic.

2.1.1 Jump detection methodology

We use high-frequency equity return data to construct realized volatility and jump risk measures. To identify jumps, we rely on economic intuition that jumps in financial markets are rare and large. This allow us to explicitly estimate the jump intensity, jump variance and jump mean.

Assuming that the price of an asset (an equity in this paper) follows a jump diffusion process. Let p_t denote the logarithmic price which follows a continuous-time jump-diffusion process defined by the stochastic differential equation as follows:

$$dp_t = \mu_t dt + \sigma_t dW_t + k_t dq_t \tag{2.1}$$

where μ_t is the instantaneous drift of the price process and σ_t is the diffusion process; with W_t a standard Brownian motion. The first two terms correspond to the diffusion part of the total variation process. The final term, $k_t dq_t$ refers to the jump component of p_t, where q_t is a counting process such that $dq_t = 1$ indicates a jump at time t, k_t is the size of jump at time t conditional on a jump occurring.

As empirical studies rely on discretely sampled returns; we denote discrete-time intraday returns on trading day t as

$$r_{t,j} = p_{t,j} - p_{t,j-1}, \qquad j = 1, \dots, M; t = 1, \dots, T \tag{2.2}$$

where $p_{t,j}$ refers to the j th intra-day log-price for day t; T is the total number of days in the sample and M refers to the number of intraday equally spaced return observations over the trading day t, which depends on the sampling frequency. As such, the daily return of the active part of the trading day is $r_t = \sum_{j=1}^{M} r_{t,j}$.

The two common measures that capture the variation in returns over the period, are the realized variation[8] and the bi-power variation. The realized variance (RV) is defined as the sum of squared intraday-returns,

$$RV_t = \sum_{j=1}^{M} r_{t,j}^2, \qquad t = 1, \dots, T \tag{2.3}$$

[8]It is not conventional to subtract the mean to compute realized variance in the high-frequency literature because the mean of the high frequency returns, say 5-min returns is close to zero. See, Barndorff-Nielsen and Shephard (2004) and Andersen et al. (2007) for more details

Where M is the sample length for jump detection (often daily). Using the theory of quadratic variation, the realized variation converges uniformly in probability to a quadratic variation process, which provides a consistent nonparametric measure of total return variation. We can re-write this as:

$$RV_t \xrightarrow{p} \int_{t-1}^{t} \sigma_s^2 \, ds + \sum_{S=q_{t-1}}^{q_t} k_S^2 , \qquad t = 1, \dots, T \tag{2.4}$$

Here $\int_{t-1}^{t} \sigma_s^2 \, ds$ is the integrated variance, and $\sum_{S=q_{t-1}}^{q_t} k_S^2$ is the quadratic variation of the jump part over the period from $t-1$ to t (often a day). Jump tests are therefore designed to estimate or detect jumps using high-frequency data.

A number of techniques have been developed to detect the existence of jumps in asset prices; For instance, Barndorff-Nielsen and Shephard (2006), Andersen et al. (2007), Lee and Mykland (2008), Aït-Sahalia and Jacod (2009), Jiang and Oomen (2008) and Podolskij and Ziggel (2010). We follow the non-parametric jump detection test developed by Barndorff-Nielsen and Shephard (2006) and Huang and Tauchen (2005) which uses the calculated realized bi-power variation to proxy the integrated variance. Since jumps are rare and are unlikely to occur in two consecutive intraday returns, when intervals are small enough, the realized bi-power variation will converge in probability to the integrated variance.[9] The difference between realized variance and bi-power variation is then an estimator of the jump variation. Bi-power variation (BV) is given by

$$BV_t = \mu_1^{-2} \sum_{j=2}^{M} |r_{t,j}| |r_{t,j-1}| , \quad t = 1, \dots, T \tag{2.5}$$

where $\mu_1 = \sqrt{2/\pi}$. Barndorff-Nielsen and Shephard (2004) show that BV consistently estimates the integrated variance when the sampling frequency goes to infinity. Therefore,

$$BV_t \xrightarrow{p} \int_{t-1}^{t} \sigma_s^2 \, ds, \qquad for\ M \to \infty \tag{2.6}$$

[9] Jumps do occur in clusters, a feature similar to volatility clustering (Novotný et al. 2015). However, Bollerslev et al. (2015) consider that by their very nature, systematic jumps are relatively rare, and as such it is not feasible to identify different jump betas for different jump sizes, let alone identify the small jumps in the first place. This assumption also maps directly into the way in which we empirically estimate jump betas for each of the individual stocks based solely on the large- size jumps.

Consequently the jump contribution to total variation is estimated from a combination of equations (2.4) and(2.6), for $M \to \infty$

$$RV_t - BV_t \to \sum_{S=q_{t-1}}^{q_t} k_s^2\,, \quad t = 1, \dots, T \tag{2.7}$$

Following Huang and Tauchen (2005), we define the jump ratio statistic

$$RJ_t = \frac{RV_t - BV_t}{RV_t}, \tag{2.8}$$

which converges to a standard normal distribution when scaled by its asymptotic variance in the absence of jumps. That is

$$ZJ_t = \frac{RJ_t}{\sqrt{\left[\left(\frac{\pi}{2}\right)^2 + \pi - 5\right]\frac{1}{M}\max\left(1, \frac{DV_t}{BV_t^2}\right)}} \xrightarrow{d} N(0,1) \tag{2.9}$$

where DV_t is the quad-power variation robust to jumps as shown in Barndorff-Nielsen and Shephard (2004) and Andersen et al. (2007). The quad-power variation is defined as

$$DV_t = M\mu_1^{-4}\left(\frac{M}{M-3}\right)\sum_{j=4}^{M}|r_{t,j-3}||r_{t,j-2}||r_{t,j-1}||r_{t,j}|, \quad t = 1, \dots, T \tag{2.10}$$

The ZJ_t statistic in equation (2.9) can be applied to test the null hypothesis that there is no jump in the return process on a trading day, t. Huang and Tauchen (2005) show that this test has very good size and power.

Following Tauchen and Zhou (2011), we further assume that there is at most one jump per day and that jump size dominates the return when a jump occurs.[10] The jump component of the realized volatility on that day is defined as:

$$J_t = sign(r_{t,j}) \times [RV_t - BV_t] \times I[ZJ_t \geq \emptyset_\alpha^{-1}] \tag{2.11}$$

where $\emptyset$ is the probability of a standard normal distribution, α is the level of significance chosen as 0.999 and $I[ZJ_t \geq \emptyset_\alpha^{-1}]$ refers to the indicator function which takes the value of one if there is a jump on a given day, and zero otherwise. Once the realized jumps have been established, we can then estimate the jump intensity, mean and volatility.

[10] See, Bollerslev et al. (2015) and Tauchen and Zhou (2011) for the asymptotic results.

2.2.1 Decomposing systematic risks: diffusion and jump components

It is common to express daily returns for an asset in terms of a factor model. In traditional capital asset pricing model (CAPM), the relationship between the expected return of an individual asset or portfolio and its systematic risk is expressed as:

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \varepsilon_{i,t} \tag{2.12}$$

Where $r_{i,t}$ is the return on stock *i*, and $r_{m,t}$ is the aggregate market return at time *t*. The slope coefficient β_i in Equation (2.12) is the systematic risk of asset *i*, and measures the responsiveness of a stock movement to the market.[11] The CAPM model basically depends on stock and market returns, which in turn, depends the underlying prices of individual stocks. It is now widely agreed in the literature that financial return volatilities and correlations are time-varying and returns follow the sum of a diffusion process and a jump process.[12]

If the return of stocks should be divided into a jump part and diffusion part certainly the risk associated with returns of securities should be decomposed into two parts also. The CAPM states that beta, a diffusion risk, is systematic and non-diversifiable. So is the jump risk when taking both diffusion process and jump process into account. The presence of jump variations in both individual assets and aggregate market affect co-variance estimations and consequently the estimations of realized beta and systematic risk. Thus it would be prudent to disentangle the jump component and the diffusion component in prices because they are basically two quite different sources of risk; see, e.g. Eraker (2004), Pan (2002), Yan (2011), Todorov and Bollerslev (2010), Bollerslev et al. (2015).

With the presence of jumps in stock prices, the CAPM model needs to be revised, as Todorov and Bollerslev (2010) suggest to incorporate the cumulative return from intervals with jumps or jump return. We use the recent work of Todorov and Bollerslev (2010) to consider the impact of potential jumps in prices on our main findings. Like Todorov and Bollerslev (2010), we decompose the factor return into part attributable to a diffusion component and a part attributable to jumps. Hence in the presence of both components, equation (2.12) becomes:

$$r_{i,t} = \alpha_i + \beta_i^c r_{m,t}^c + \beta_i^d r_{m,t}^d + \varepsilon_{i,t} \tag{2.13}$$

[11]The standard CAPM beta, $\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)}$

[12] See, for example, Press (1967), Merton (1976), and Ball and Torous (1983) and among others.

Where $r_{i,t}$ is the stock return on stock i, $\alpha_i$is a drift term, market risk $(r_{m,t})$ is modelled as a combination of a diffusion $(r^c_{m,t})$ and jump component $\left(r^d_{m,t}\right)$, and β^c_i and β^d_i denotes the responsiveness of each stock's movement to the diffusion and jump components of market risk and ε_i denotes the idiosyncratic term which may also made up a diffsuion and jump component. This decomposition is interesting because standard factor models of risk implicitly assume that an asset's systematic risk is uncorrelated with jumps in the market (i.e. that the asset's beta does not change on days when the market experiences a jump). Equation (2.12) does not distinguish between the diffusion and jump components of total return, but does decompose total returns into systematic $(\beta_{i,t} r_{m,t})$ and nonsystematic $(\alpha_i + \varepsilon_{i,t})$ components. Any market jump is embedded in $r_{m,t}$, while any nonsystematic jump unique to firm i is included in the error term. When the systematic risks exposure of a firm to both diffusion and jump price movements are identical, i.e. $\beta^c_{i,t} = \beta^d_{i,t}$, then, the two-factor market of (3.13) model collapses to the usual one-factor market model, which relates the stock return $r_{i,t}$ to the total market return $r_{m,t} = r^c_{m,t} + r^d_{m,t}$. The restriction that $\beta^c_{i,t} = \beta^d_{i,t}$ implies that the asset responds identically to market diffusion and jump price movements, or intuitively that the asset and the market co-move in the same manner during "normal" times and periods of "abrupt" market moves. If, on the other hand, $\beta^c_{i,t}$ and $\beta^d_{i,t}$ differ, empirical evidence for which is provided below, the cross-sectional variation in the diffusion and jump betas may be used to identify their separate pricing. The literature suggests that the two betas are not the same, i.e. the reactiveness of an asset return of the two components of systematic risk can be different, denoted by $\beta^c_{i,t}$ and $\beta^d_{i,t}$ respectively.

2.2.2 Diffusion and jump betas

Given that market returns contain two components, both of which display substantial volatility and which are not highly correlated with each other, the possibility that different types of stocks may have two different betas corresponding to the two components occurs. The decomposition of the return for the market into separate diffusion and jump components that formally underlie $\beta^c_{i,t}$ and $\beta^d_{i,t}$ in equations (2.13) are not directly observable. Instead, we assume that prices are observed at discrete time grids of length M over the active trading day$[0, T]$. To allow for the presence of jumps in the price process, Todorov and Bollerslev (2010) consider the following specification for stock *i* and aggregate market *m*. The log price process evolves as follows[13]:

For the market,

$$r_{m,t,j} \equiv dp_{m,t} = \alpha_{m,t}dt + \sigma_{m,t}dW_{m,t} + k_{m,t}dq_{m,t} , \tag{2.14}$$

and for the stock $i = 1, \dots, \mathrm{N}$,

$$r_{i,t,j} \equiv dp_{i,t} = \alpha_{i,t}dt + \beta_{i,t}^{c}\sigma_{m,t}dW_{m,t} + \beta_{i,t}^{d}k_{m,t}dq_{m,t} + \sigma_{i,t}dW_{i,t} + k_{i,t}dq_{i,t}, \tag{2.15}$$

where, $W_{m,t}$ and $W_{i,t}$ are standard Brownian motions for the market and asset *i*; $\alpha_{m,t}$ and $\alpha_{i,t}$denote the diffusive volatility of the aggregate market and stock *i*, respectively; and $q_{m,t}$ and $q_{i,t}$ refer to the pure jump Levy processes in the aggregate market and stock *i*, respectively. $\beta_{i,t}^{c}$ and $\beta_{i,t}^{d}$ measure the responsiveness of an individual stock to the diffusion and jump component of market risk. In this framework,$[\beta_{i,t}^{c} , \beta_{i,t}^{d}]$ is assumed constant throughout each day but can change from day to day.

In order to disentangle the $\beta_{i,t}^{c}$ and $\beta_{i,t}^{d}$, Todorov and Bollerslev (2010) propose a non-parametric beta estimation technique using multipower co-variation/variation between the returns of individual stocks and the market portfolio for given diffusion and jump components respectively. They show that $\beta_{i,t}^{c}$ and $\beta_{i,t}^{d}$ can be theoretically identified. .

To begin, consider the estimation of diffusion betas. Suppose that neither the market or nor stock *i*, jumps, so that $q_{m,t} \equiv 0$ and $q_{i,t} \equiv 0$ almost surely. For simplicity, suppose also that the drift terms in equations in (2.14) and (2.15) are both equal to zero, so that,

$$r_{i,t,j} = \beta_{i,t}^{c} r_{m,t,j} + \widetilde{r_{i,t,j}} , \quad \text{where } \widetilde{r_{i,t,j}} \equiv \int_{t-1}^{t} \sigma_s^2 \, ds ,$$

for any $\mathrm{j} \in [\mathrm{t}-1, \mathrm{t}]$. In this situation, the ratio of the intra-day covariance between an asset and the market, and the market with itself will estimate diffusion beta using high-frequency intraday returns. The diffusion beta is given by

$$\beta_{i,t}^{c} = \frac{\sum_{j=1}^{m} r_{i,t,j}\, r_{m,t,j}}{\sum_{j=1}^{m} \left(r_{m,t,j}\right)^2} \tag{2.16}$$

[13] The notation here is simplified relative to that in Todorov and Bollerslev (2010); See their article for more details.

In general, of course, the market may have jump over the $[t-1, t]$ time-interval and the drift terms are not identically equal to zero. Meanwhile, it follows readily by standard arguments that for $m \rightarrow \infty$, the impact of the drift terms are asymptotically negligible. However, to allow for the possible occurrence of jumps, the simple estimator defined above needs to be modified by removing the jump components. In particular, following Todorov and Bollerslev (2010), we consider their ratio statistics for the discretely sampled data series which consistently estimate the diffusion beta for $m \rightarrow \infty$, under very general conditions. These are:

$$\hat{\beta}_{i,t}^{c} = \frac{\sum_{j=1}^{m} r_{i,t,j}\, r_{m,t,j}\, \mathbb{I}_{\{|r_{t,j}| \leq \theta\}}}{\sum_{j=1}^{m} \left(r_{m,t,j}\right)^{2} \mathbb{I}_{\{|r_{t,j}| \leq \theta\}}} \quad , \quad i = 1, \dots, N. \tag{2.17}$$

Where, $\mathbb{I}_{\{|r_{t,j}| \leq \theta\}}$ is the indicator function,

$$\mathbb{I} = \begin{cases} 1 & if \; \{|r_{t,j}| \leq \theta\} \\ 0 & Otherwise \end{cases} \tag{2.18}$$

based on the truncation level, θ, for diffusion component.

Now, we consider the estimation of jump beta. The actually observed high-frequency returns contain both diffusive and jump risk components. However, by raising the high-frequency returns to powers of orders greater than two, the diffusion components become negligible, so that the systematic jump dominates asymptotically for $m \rightarrow \infty$.[14] As formally shown in Todorov and Bollerslev (2010), the following estimator is indeed consistent for jump beta when there is at least one significant jump in the market portfolio for the given estimation window for $m \rightarrow \infty$.

$$\hat{\beta}_{i,t}^{d} = \operatorname{sign}\left\{\sum_{j=1}^{m} \operatorname{sign}\{r_{i,t,j}\, r_{m,t,j}\} \left|r_{i,t,j}\, r_{m,t,j}\right|^{\tau}\right\} \times \left(\frac{\left|\sum_{j=1}^{m} \operatorname{sign}\{r_{i,t,j}\, r_{m,t,j}\} \left|r_{i,t,j}\, r_{m,t,j}\right|^{\tau}\right|}{\sum_{j=1}^{m} \left(r_{m,t,j}\right)^{2\tau}}\right)^{\frac{1}{\tau}}, \tag{2.19}$$

Here, the power τ is restricted to be ≥ 2 so that the diffusion price movements do not matter asymptotically. The sign in equation (2.19) is taken to recover the signs of jump betas that are eliminated when taking absolute values.

[14] The basic idea of relying on higher orders powers of returns to isolate the jump component of the price has previously been used in many other situations, both parametrically and nonparametrically; see e.g., Barndorff-Nielsen and Shephard (2003).

Following Todorov and Bollerslev (2010) and Alexeev et al. (2017) we set the parameter values for θ, ϖ, and α estimate the $\hat{\beta}_{i,t}^{c}$ and $\hat{\beta}_{i,t}^{d}$ on both monthly and daily basis. For estimating $\hat{\beta}_{i,t}^{c}$ and $\hat{\beta}_{i,t}^{d}$, the truncation threshold, $\theta = \alpha\Delta_n^{\varpi}$, uses $\varpi = 0.49$ and $\alpha \geq 0$, suggesting that the threshold values may vary across stocks and across different estimation window. The threshold for the diffusion price movement, $\theta = \alpha_i^c = \sqrt[3]{BV_i^{[0,T]}}$ for $\hat{\beta}_{i,t}^{c}$ suggests that the diffusion component discards movements over three standard deviation away from mean, and thus unlikely to be associated with diffusion price movements, where, $BV_i^{[0,T]}$ is the bi-power variation of the i-th stock at time $[0,T]$; the value of $\tau = 2$ for equation (2.19).

2.3. Sample and data

The sample consists of high frequency stock price data for 50 of the 63 commercial banks traded on the Tokyo Stock Exchange (TSE) for the period January 2001 through December 2012, a total of 3053 trading days (There were 13 banks where the data were not available). The sample period allow us to investigate the transmission of shock in Japanese market in periods of calm and crisis (subprime and global financial crisis).The list of banks in the sample is provided in Table 2.1. Data are extracted from the Thompson Reuters Tick history (TRTH) database available via SIRCA. We use the Nikkei 225 index as a proxy for the market portfolio.[15]

The stock prices are sampled at a five minute frequency, as is standard in a large part of the high frequency literature (Alexeev et al. 2017,Dungey et al. 2009 , Bollerslev et al. 2009). The choice of 5-minute sampling frequency reflects a trade-off between using all available data and avoiding the impact of market microstructure effects, such as infrequent or nonsynchronous trading; the issue of optimal sampling frequency choice is an ongoing research agenda, see for example Zhang (2011). Unlike the more commonly investigated US and European markets, daily trading on the TSE is interrupted by a lunch break, trading between 09:00 am-11:00 am and 12:30 pm-3:00 pm local time. We sample prices from 9:05 am-11:00 am and 12.35 pm-3.00 pm, with overnight and over-lunch returns excluded from the data set.[16] Missing data at 5-minute intervals are filled with the previous price creating a zero return. Hansen and Lunde

[15]The Nikkei is a price-weighted index, consisting of 225 stocks in the first section of the TSE selected subject to certain industry-balance considerations. It represents the 50 % of the total market capitalization of the TSE.
[16] We are only concerned with the active trading period, and overnight information is beyond the scope of this study.

(2006) show that this previous tick method is a sensible way to sample prices in calendar time. These restrictions result in a final sample of 2866 active trading days (in 144 months), each consisting of 53 intraday day 5 min-returns for a total of 1, 61,809 observations.

Table 2.2 presents the market capitalization and turnover ratio on TSE over the sample. Market capitalization was rising steadily prior to the global financial crisis of 2008-2009 and the European debt crisis period, from April 2010 until the end of the sample market capitalization rose. By 2012 it was at a level similar to that at the beginning of the sample. The turnover ratio peaked in 2007, and has since declined.

Table 2.1: List of banks

No	Banks	No	Banks	No	Banks
1	Aichi Bank	21	Hiroshima Bank	41	Shinsei Bank
2	Akita Bank	22	Hokkoku Bank	42	Shizuoka Bank
3	Aomori Bank	23	Hokuetsu Bank	43	Sumito Mitsui Financial Gp
4	Aozora Bank	24	Hokuhoku Financial Gp.	44	Suruga Bank
5	Awa Bank	25	Hyakugo Bank	45	Tochigi Bank
6	Bank Of Iwate	26	Hyakujushi Bank	46	Toho Bank
7	Bank Of Kyoto	27	Iyo Bank	47	Tokoyo Tomin Bank
8	Bank Of Nagoya	28	Joyo Bank	48	Yachiyo Bank
9	Bank Of Okinawa	29	Juroku Bank	49	Yamagata Bank
10	Bank Of The Ryukyus	30	Kagoshima Bank	50	Yamaguchi Finl.G.
11	Bank Of Yokohama	31	Keiyo Bank		
12	Chiba Bank	32	Miyazaki Bank		
13	Chugoku Bank	33	Musashino Bank		
14	Daishi Bank	34	Nanto Bank		
15	Fukui Bank	35	Nishi-Nippon City Bank		
16	Fukuoka Financial Group	36	North Pacific Bank		
17	Gunma Bank	37	Ogaki Kyoritsu Bank		
18	Hachijuni Bank	38	Oita Bank		
19	Higashi Nippon Bank	39	San-In Godo Bank		
20	Higo Bank	40	Seventy-seven Bank		

Table 2.2: Market capitalization and turnover of analysed stock market

Stock Exchange (Country)		
Tokoyo(Japan)	Stock market capitalization	Turnover ratio
2001	60.67	72.37
2002	54.10	73.06
2003	62.05	85.13
2004	74.55	98.84
2005	91.25	119.79
2006	105.95	135.45
2007	104.49	142.74
2008	86.09	140.84
2009	67.10	127.10
2010	74.60	114.50
2011	68.58	108.90
2012	61.80	99.80

2.4. Empirical results

In this section, we present the empirical results. In section 3.4.1, we start by examining large discontinuous changes, known as jumps, in Japanese bank stock prices. In section 3.4.2 and 3.4.3, we then examine empirically how individual stock prices respond to diffusion, jump market moves in the context of single-factor model, and relate their variation to firm characteristics and economic conditions. Finally, in section 3.4.4, we examine how different systematic betas explain the stock returns.

2.4.1 Evidence on asset-prices jumps

Empirical evidence suggests that asset prices display infrequent large movements that are too big to be Gaussian shocks. In the Figure 2.1, we plot the time series of intraday returns on a broad market index for the period 2001-2012. Occasional large spikes in the series suggest the presence of large moves (jumps). Consistent with this evidence, the kurtosis of market returns is 29, relative to 3 for normal distribution, as shown in the Table 2.3. Figure 2.2 shows the sample measures of daily-realized volatility, bipower variation and jumps for the Japanese stock index. Market volatility was particularly high during the second half of 2008, associated with the disruptions to global markets around the period of the failure of Lehman Brothers, the rescue of AIG and other financial institutions. The plots reveal interesting volatility clustering and time variation of jump size along the sample period. The bottom panel of Figure 2.2 shows that, many of the largest realized volatilities are directly associated with jumps in the underlying price process.

Using the Barndorff-Neilsen and Shepard test we find a total number of 272 jump days in the Nikkei index in the sample period. The proportion of jump days of the total is 9.4%, consistent with the proportions reported for other developed markets, including for the S&P500, 8.54% jump days in Todorov and Bollerslev (2010) from 2001 to 2005 and 3.5% jump days in. Alexeev et al. (2017) for 2003 and 2011. Of the 144 months in our sample, 115 contain at least one jump day. The results suggest that the frequencies of jump occurrence in Japanese equity market are slightly higher than the US market.

Table 2.3:Summary statistics for daily volatilities and jumps (figure scaled by 100 with the exception of skewness and kurtosis)

	Mean	**Median**	**Max**	**Min**	**Std. Dev.**	**Skewness**	**Kurtosis**
r_t	-0.0005	0.0006	3.2727	-4.3376	0.1330	-0.243	29.466
RV_t	0.0013	0.0004	0.0952	0.0000	0.0044	11.900	186.429
$\sqrt{RV_t}$	0.2693	0.2119	3.0857	0.0049	0.2472	3.942	29.964
BV_t	0.0012	0.0003	0.0998	0.0000	0.0043	13.111	231.500
$\sqrt{BV_t}$	0.2435	0.1847	3.1595	0.0034	0.2452	3.994	31.201
J_t	0.0002	0.0000	0.0173	0.0000	0.0006	15.706	362.712
$\sqrt{J_t}$	0.0905	0.0674	1.3151	0.0000	0.1032	3.029	22.806

Table 2.3 reports the summary statistics for daily volatilities and jumps for the Nikkei 225 stock index. The mean realized volatility is $(\sqrt{RV})$ is 0.27%, while average bi-power variation $(\sqrt{BV})$ is 0.24%. The average absolute jump size $(\sqrt{J})$ is 0.09%. The unconditional distributions of both volatility measures and jumps (J_t), are highly skewed and leptokurtic, with the relative jump measure, J_t, clearly indicating a more positive skewness and a higher degree of leptokurtosis than the daily realized volatilities, and suggesting that they occur on a small number of occasions with large impact on the Japanese index return.

From Table 2.3, we observe that, for the equity index, approximately 85% (BV_t/RV_t) is due to diffusion components of returns and the jump contribute 14% (J_t/RV_t) of realized variation. Andersen et al. (2007) find a similar jump contribution to RV for the S&P 500 index.

Table 2.4:Yearly statistics of significant jumps

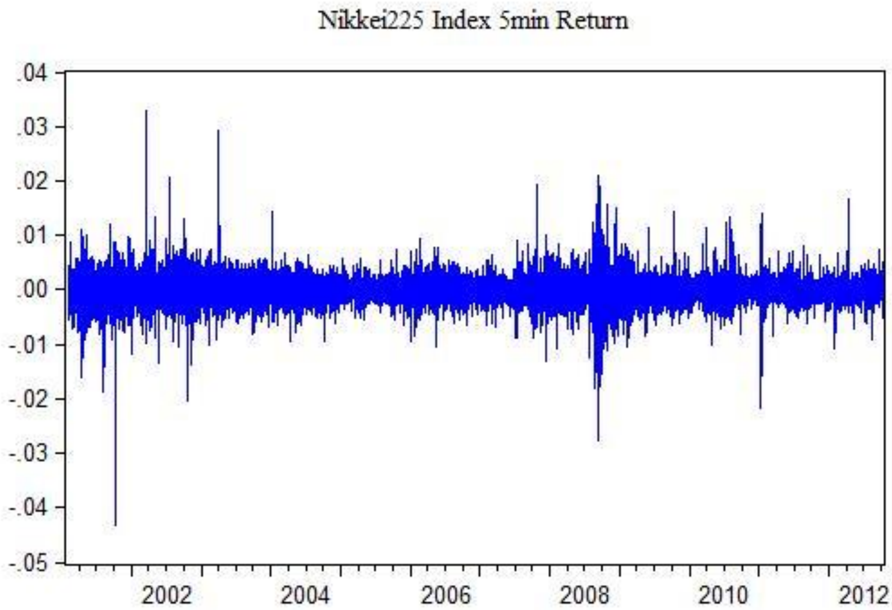
Year	No of Jump days	No of Jump months
2001	14	8
2002	26	11
2003	14	7
2004	39	11
2005	33	12
2006	20	11
2007	10	6
2008	17	6
2009	25	11
2010	30	11
2011	23	10
2012	21	11
Total no of Jumps	272	115

Note: number of jumps denote the number of days with jumps. Number of jump months denotes months containing with at least one jump day.

Table 2.4 provides an annual picture of the identified jump months for the period January 2001-December 2012.[17] The number of jumps ranges from 10 to 39 in the Japanese market. The prevalence of jumps decreases during the period of most global financial stress in 2007 and 2008, consistent with Chatrath et al. (2014) and Dungey et al. (2014) who show that jump frequency does not increase in periods of stress. Overall, the results show that the numbers of jumps does not vary a great deal across the sample period – in most years the majority of months contain jumps. A plausible explanation for our findings is that investors may underreact to new about shocks as they already revising their expectations of the aggregate economy using the information from the economy. Patton and Verardo (2012) propose a simple learning model in which investors use information on firm announcements to revise their expectations about other firms and the entire economy. Another possible explanation is that during the crisis period the threshold of jump identification increases with the overall market volatility. Therefore, some large price discontinuities, generally classified as jumps during the calm period, may be classified as continuous movements during the crisis period.

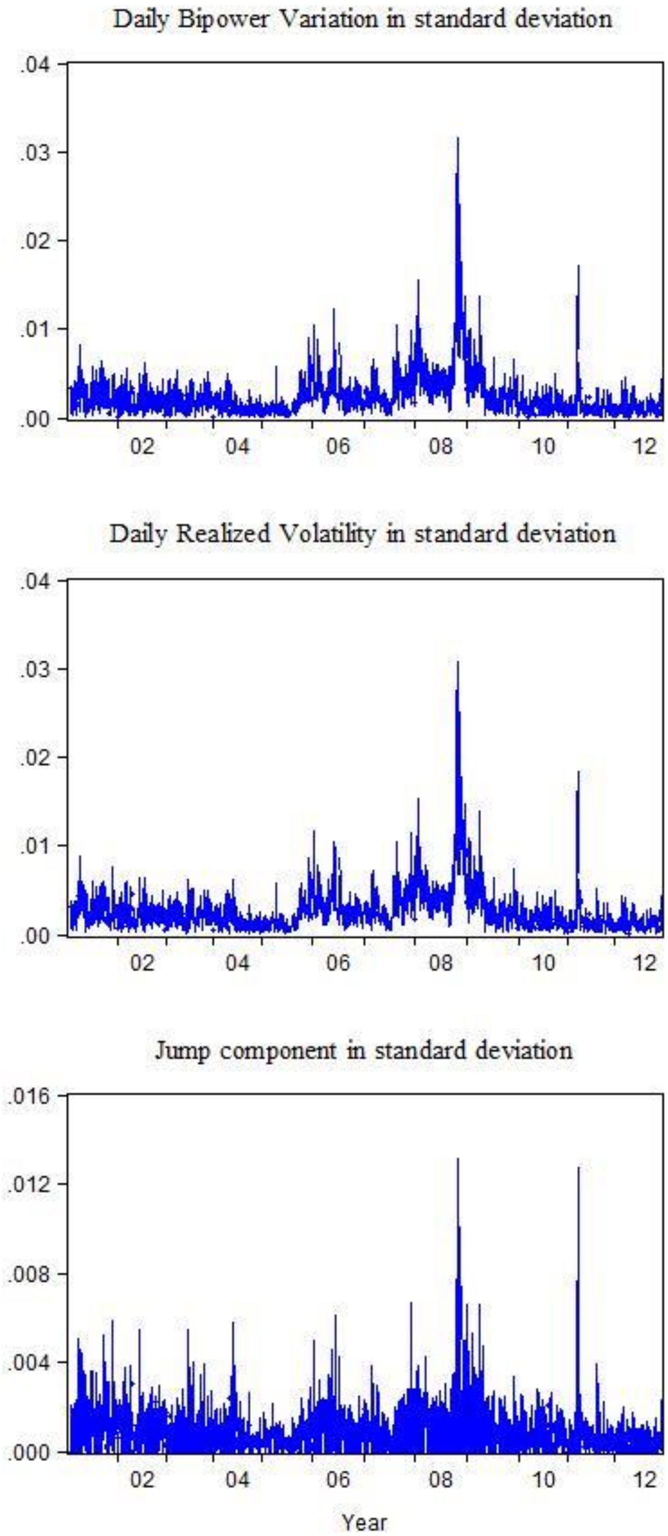
[17] Using high frequency data, a number of large literatures have established a link between jumps and macroeconomic news. See, for example, Dungey et al. (2009), Lahaye et al. (2011), Evans (2011), Gilder et al. (2014), and among others. Appendix Table A1 reports a complete list of theses significant jump days. A formal evaluation of the link between jumps and news in a more rigorous manner is surely valuable to pursue, but is beyond the scope of the study.

Figure 2:1: Intraday returns for the Nikkei 225 index at 5 minute frequency for 2001 through 2012



Motivated from these identified jump days (with their corresponding jump months) we now estimate monthly diffusion systematic risk (diffusion beta) and jump systematic risk (jump beta) for the sample period. Particularly, we estimate the diffusion and discontinuous betas of 50 listed Japanese banks on a daily and month basis using the Todorov and Bollerslev approach. We then investigate the relationship between different betas and other firm characteristics.

Figure 2:2: Realized volatilities, bi-power variations and jumps



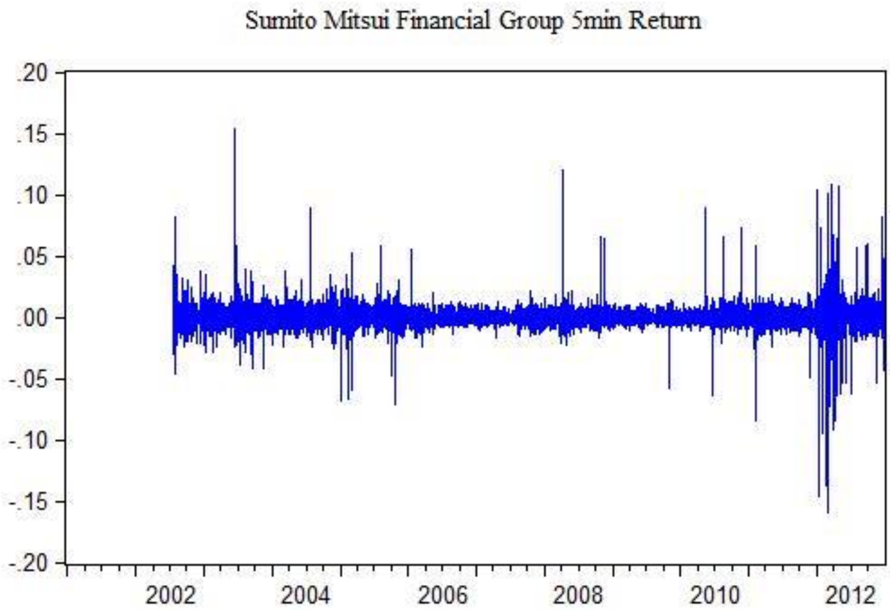
A. A case study: the Sumito Mitsui Financial Group

To make the methodology concrete this subsection presents a case study for a particular bank. The results in Section 3.4.3 identified that the bank with both the highest diffusion and jump beta in the sample banks was Sumito Mitsui Finance Group (SMFG). We present a brief case study of this bank as an illustration of firm level analysis using the tools presented in this paper. Figure 2.3 plots the intraday prices and returns for the stock at 5 minute frequency. The price for SMFG peaked at the end of 2007 and subsequently declined, stabilizing near the end of the sample period.

SMFG is a bank holding company, associated with the Sumitomo Mitsui Banking Corporation, which in turn the second largest bank in Japan (after Mitsubishi) and ranked 31st largest bank in the world in March 2015 with USD55billion of assets.[18] This bank's operations include retail, corporate, and investment banking. SMFG has some 500 domestic branches and another 20 branches abroad. Other units of SMFG include credit card company Sumitomo Mitsui Card, brokerage SMBC Friend Securities, management consulting firm Japan Research Institute, and Sumitomo Mitsui Finance and Leasing. In the US it operates California-based Manufacturer's Bank. The bank has a total capital ratio of 15.02% and a tier I ration of 11.15%. Of the three mega Japanese banks, SMFG has the highest total capital adequacy ratio.

[18] Ranking from www.relbanks.com.

Figure 2:3: Prices and returns for the Sumito Mitsui Financial Group



2.4.2 Decomposing systematic risk into diffusion and jump components

We undertake our analysis on the estimates of diffusion and jump betas at a monthly, and not daily, frequencies as both Todorov and Bollerslev (2010) and Alexeev et al. (2017) show that daily betas do not provide analytically tractable results.[19]

Table 2.5: Average monthly beta

		95% confidence interval			95% confidence interval	
Banks	**Beta C**	**CI_low**	**CI_up**	**Beta J**	**CI_low**	**CI_up**
Aichi Bank	0.10	0.018	0.180	0.78	0.765	0.804
Akita Bank	0.14	0.046	0.207	0.77	0.753	0.795
Aomori Bank	0.09	0.000	0.146	0.64	0.620	0.651
Aozora Bank	0.38	0.266	0.496	1.14	1.088	1.191
Awa Bank	0.16	0.080	0.235	0.82	0.801	0.843
Bank of Iwate	0.15	0.063	0.224	0.77	0.748	0.796
Bank of Kyoto	0.40	0.318	0.486	0.92	0.902	0.946
Bank of Nagoya	0.21	0.123	0.296	0.93	0.903	0.955
Bank of Okinawa	0.10	0.014	0.174	0.70	0.676	0.715
Bank of The Ryukyus	0.24	0.149	0.318	0.76	0.734	0.779
Bank of Yokohama	0.63	0.538	0.720	1.09	1.067	1.123
Chiba Bank	0.65	0.554	0.735	1.16	1.141	1.185
Chugoku Bank	0.29	0.211	0.372	0.85	0.827	0.869
Daishi Bank	0.21	0.118	0.288	0.92	0.904	0.940
Fukui Bank	0.10	0.011	0.165	0.73	0.713	0.747
Fukuoka Financial Group	0.68	0.587	0.782	1.47	1.433	1.508
Gunma Bank	0.44	0.348	0.529	1.07	1.051	1.099
Hachijuni Bank	0.39	0.297	0.472	1.08	1.058	1.102
Higashi Nippon Bank	0.15	0.041	0.224	0.74	0.720	0.763
Higo Bank	0.18	0.099	0.262	0.81	0.793	0.828
Hiroshima Bank	0.33	0.241	0.411	0.95	0.931	0.974
Hokkoku Bank	0.17	0.088	0.250	0.83	0.818	0.848
Hokuetsu Bank	0.10	-0.014	0.157	0.70	0.673	0.726
Hokuhoku Finl.Gp.	0.41	0.298	0.515	1.21	1.180	1.250
Hyakugo Bank	0.23	0.135	0.302	0.89	0.871	0.915
Hyakujushi Bank	0.22	0.133	0.302	1.02	0.999	1.047
Iyo Bank	0.32	0.237	0.404	0.93	0.905	0.947
Joyo Bank	0.40	0.306	0.487	1.12	1.098	1.142
Juroku Bank	0.25	0.160	0.334	0.94	0.914	0.958
Kagoshima Bank	0.20	0.114	0.278	0.81	0.794	0.827

[19] Estimates of diffusion and jump betas are computed on a month-by-month basis. High frequency 5 minute data permits the use of 1-month non overlapping windows to analyses the dynamics of our systematic risk estimates. We also estimated the daily betas and the daily betas estimates are obviously somewhat noisy and difficult to interpret. Meanwhile, the estimated monthly betas appear much more stable, while still showing interesting and clearly discernable pattern over time. Therefore, we concentrate on monthly betas.

Keiyo Bank	0.25	0.149	0.316	0.84	0.824	0.865
Miyazaki Bank	0.09	0.002	0.162	0.62	0.609	0.640
Musashino Bank	0.34	0.247	0.416	0.99	0.971	1.015
Nanto Bank	0.01	-0.046	0.053	0.50	0.499	0.505
Nishi-Nippon City Bank	0.34	0.242	0.442	1.16	1.121	1.198
North Pacific Bank	0.08	0.289	0.496	1.13	0.361	1.183
Ogaki Kyoritsu Bank	0.20	0.116	0.281	0.91	0.878	0.935
Oita Bank	0.11	0.030	0.194	0.77	0.749	0.783
San-In Godo Bank	0.24	0.159	0.325	0.90	0.875	0.924
Seventy-Seven Bank	0.41	0.316	0.498	1.06	1.036	1.092
Shinsei Bank	0.50	0.383	0.620	1.35	1.310	1.393
Shizuoka Bank	0.62	0.536	0.702	1.06	1.033	1.081
Sumito Mitsui Finl.Gp	0.88	0.768	0.977	1.50	1.463	1.543
Suruga Bank	0.44	0.351	0.533	1.04	1.019	1.068
Tochigi Bank	0.13	0.039	0.198	0.69	0.668	0.706
Toho Bank	0.15	0.058	0.224	0.73	0.703	0.754
Tokoyo Tomin Bank	0.36	0.260	0.451	1.09	1.065	1.119
Yachiyo Bank	0.14	0.045	0.230	0.46	0.431	0.489
Yamagata Bank	0.09	0.016	0.162	0.71	0.697	0.720
Yamaguchi Finl. Gp	0.45	0.361	0.538	1.21	1.187	1.242

Table 2.5 reports the average monthly diffusion and jump beta estimates for each of the 50 banks in the sample along with their respective 95% confidence intervals. The jump betas exceed the diffusion beta for every institution. Using the corresponding 95% confidence intervals in Table 2.5, we find no evidence of overlapping interval between the jump betas, $\hat{\beta}_i^j$ and diffusion betas, $\hat{\beta}_i^c$ for any stock.

The highest betas are observed for Sumito Mitusui Financial Group, with a diffusion beta, $\hat{\beta}_i^c$ of 0.88, and jump beta $\hat{\beta}_i^j$ of 1.50. The lowest diffusion beta, $\hat{\beta}_i^c$ is 0.01 for the Nanto Bank, $\hat{\beta}_i^j$ is 0.46 for the Yachiyo bank.

The diffusion betas, are below unity for all Japanese banks during the sample period except for the Sumito Mitusui Financial Group, which has a beta very close to the market beta. This implies that stock returns of Japanese banks associated with diffusion market movement respond less to aggregate market. The issue still remains as to why the average diffusion beta values are on the whole much lower than was expected in finance theory. One of the possible reasons of our findings is that these firms stock might not have sufficient trading volume to respond sufficiently to changes in the market. If high proportions of these companies' stocks are held by parties such as government, institutions or other companies who are not interested in trading actively, the returns of these companies may not be as sensitive to shocks in the market. The result is that these firms' returns might become less correlated with the market returns, and therefore have a lower beta value. Alternatively, the lower beta values may result from the market becoming more volatile over time. Over the past decades, there have been increasing numbers of IT and telecommunications listing in the stock market. These companies' stocks are considered as highly volatile stocks. As such, the banking industry may have become relatively less volatile due to the presence of these highly volatile stocks. Since the beta values measures the relative volatility in stock returns between individual companies and the market, the beta values for these stocks may indeed have fallen.

As expected, the resulting values jump betas, $\hat{\beta}_i^j$ are higher than the diffusion betas, $\hat{\beta}_i^c$, consistent with the small existing literature for firms in the US in Alexeev et al. (2017), Bollerslev et al. (2015), Todorov and Bollerslev (2010). The results for the Japanese banks are also similar to those for the Indian banks recorded in Sayeed et al. (2017) in that the average diffusion beta is generally smaller than one, which implies that in response to the diffusive market movements, the returns of banking stocks move less than the market return for the wider variety of stocks contained in the CNX500 index, but the diffusion beta for Japanese banks indicates considerably more defensive capacity than evident in the Indian banks. This result supports the notion that the returns on individual stocks are most strongly correlated with market returns on days when the market experiences a jump (as jumps are associated with news arrival). Across individual stocks, 40% of the banks have jump betas higher than the market beta.

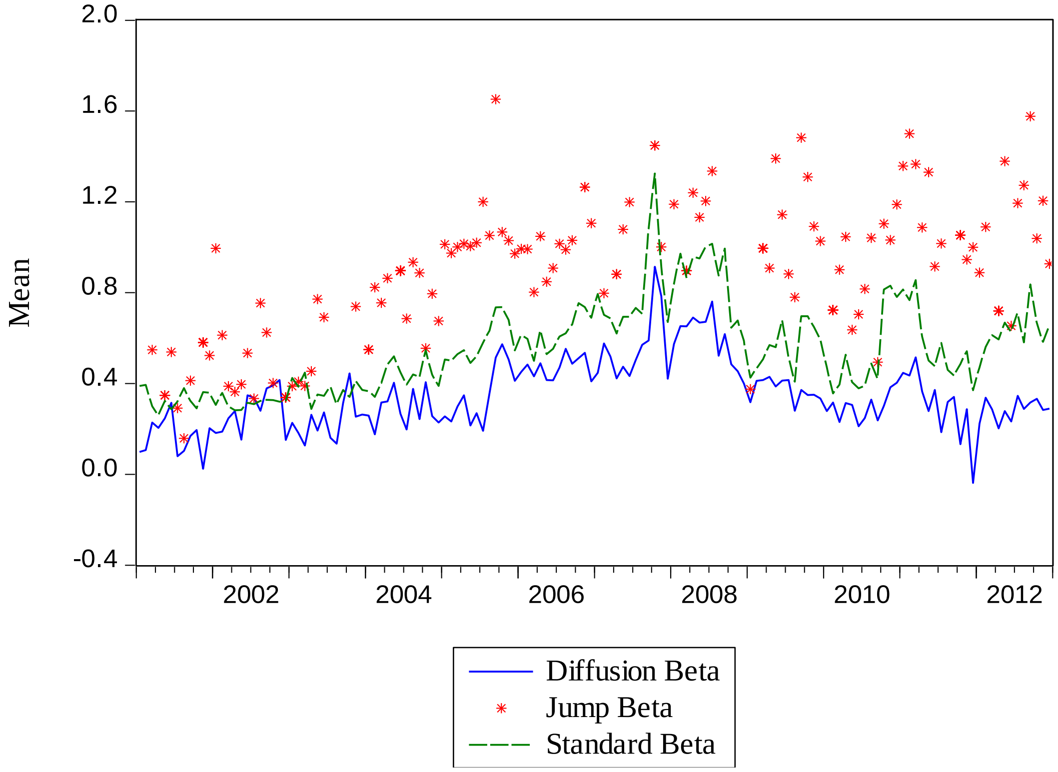
Figure 2.4 plots the cross-sectional average of the betas estimated for the standard single factor CAPM model, and the diffusion, and jump betas. It is immediately apparent from Figure 2.4 that in every case where jumps are present, the Japanese banks have a jump beta which exceeds the diffusion beta estimated for that month, on average by 0.75. The sample contains two periods of readily identifiable stress - the first in the third quarter of 2008 associated with the bankruptcy of Lehman Brothers, and the second in the first half of 2010 associated with the Greek debt crisis - and in both of these periods the gap between the diffusion and jump betas reduces. That is, there is more attention paid to volatility risk (the diffusion component of the systematic risk) in the market than jump risk caused by news. This can be partly explained by the high market volatility during the crisis periods. During times of high market stress, the overall market environment becomes relatively more important than unexpected news shocks to the system. The reaction to frequent unexpected news during stressed market times may be a feature of the overall market conditions. The results for the Japanese banks are similar to those for the US financial sector stocks recorded in Gajurel (2015) in that there is a consistently positive gap between the jump and diffusion betas for these stocks, but the diffusion beta for Japanese banks indicates considerably more defensive capacity than evident in the US financial sector. Overall, the plot demonstrates that the diffusion beta is generally lower than the standard CAPM estimate, but that the jump beta can sometimes be considerable higher. If the jump beta is viewed as the response to unexpected news entering the market, following the Patton Patton and Verardo (2012) reasoning, then this supports the much faster reaction to new information sufficient to disrupt market pricing than to the evolution of information through the diffusion price process. The difference in the estimated diffusion and jump betas estimated leads us to consider the importance of segregating these results for portfolio diversification.

2.5. Firm-level determinants of beta

A large literature in corporate finance has established that the systematic risk of a firm can be explained by a number of variables including firm size, profitability, leverage, and capital ratio.[20] Breen and Lerner (1973) argued in the context of decision making that changes in firm's financing, investing and operating decisions can influence its stock return and risk characteristics, in particular, the beta.

[20] See, for example, Hamada (1972), Mandelker and Rhee (1984), Ang et al. (1985), Amit and Livnat (1988), Scherrer and Mathison (1996), Saunders et al. (1990), Anderson and Fraser (2000), Hong and Sarkar (2007), Lee and Jang (2007), Campbell et al. (2009) and among others.

Figure 2:4:Cross-section monthly mean betas for continuous and jump months



Influential variables from the existing literature include leverage, which has a positive relationship with beta, for example Hamada (1972) and Mandelker and Rhee (1984), with Buiter and Rahbeir (2012) specifically signalling the potential systemic risk of high leverage in the banking sector. Hong and Sarkar (2007) also find that beta is an increasing function of leverage.

The effect of size on bank systematic risk is debated. While Demsetz and Strahan (1997) find that large banks tend to diversify their business more efficiently and are less prone to bankruptcy, Saunders et al. (1990) and Anderson and Fraser (2000) find that bank systematic risk increases with bank size as large banks could be more sensitive to general market movements than small banks.

By maintaining a capital buffer to absorb losses that may arise from unexpected shocks higher capital ratios are expected to decrease bank beta; representing higher bank solvency and lower perceived risk (Furlong and Keeley 1989; Keeley and Furlong 1990). Prior empirical studies also provide evidence of an inverse relationship between profitability and systematic risk (Logue and Merville 1972; Scherrer and Mathison 1996). Other work, Borde et al. (1994), finds a positive relationship between return on assets and beta during the period, 1988-1991, for US insurance companies, indicating that finance industries with higher profitability are exposed to greater systematic risk because they are be more profitable when taking more credit risks in business.

Based on the above discussion, we anticipate the following relationships between beta and these five explanatory variables; that beta increases with leverage, increases with bank size and with profitability, but decreases with higher capital ratios. We now proceed to investigate these relationships for both jump and diffusion systematic risk using the following regression framework.

$$\beta_{i,t} = \alpha_0 + \sum_{i=1}^{m} \gamma X_{i,t} + \sum_{t=1}^{2002-2012} \theta_t (time\ dummies) + \mu_{i,t} \tag{2.20}$$

where $\beta_{i,t}$ = either diffusion beta ($\hat{\beta}^c$) or Jump beta ($\hat{\beta}^j$) for bank i, at period t; $X_{i,t}$ represents the firm characteristics variables -- firm size, profitability, debt leverage, and capital ratio -- and $\mu_{i,t}$ is the model residual. We also include the time dummies to control for macro-level shocks and unobserved time heterogeneity. The monthly firm characteristics data come from the DataStream database. Following previous studies, we measure firm size by the market value of equity. Profitability is computed as earnings before interest, taxes, depreciation, & amortization over total assets. Leverage is the ratio of total debt to total assets. The capital ratio is measured as book value of equity divided by total assets. The descriptive statistics for bank characteristics variables are presented in Table 2.6.

Panel B of Table 2.6 reports the correlation matrix amongst all variables amongst all variables including the standard on factor, jump and diffusion beta estimates. The three betas are positively and highly correlated with each other (with values ranging from 0.67 to 0.80), as evident in Figure 2.4[21]. Standard beta is highly correlated with diffusion beta and jump beta with correlation coefficients of 0.80 and 0.67 respectively. In terms of firm characteristics variables, diffusion beta, and jump beta are positively correlated to size, leverage and profitability. Multicollinearity amongst the firm characteristics variables is limited to 0.38, between leverage and firm size.[22]

[21] To ease our analysis we exclude months for which we do not find a significant jump in the market.
[22] As a rule of thumb, multicollinearity is likely to exist when the independent variables are highly correlated (i.e., r = 0.80 and above (Gujarati and Porter 2009).

Table 2.6: Descriptive statistics and correlation matrix

Panel A: Descriptive statistics of the firm characteristics

Variable	Obs	Mean	Std. Dev.	Median	25th percentile	75th percentile
Firm size	6510	8.20	0.34	8.16	7.95	8.42
Profitability (%)	6450	12.08	16.30	14.17	10.47	17.99
Leverage (%)	6585	94.24	1.41	94.35	93.58	95.13
Capital ratio (%)	6585	5.96	3.10	5.47	4.58	6.30

Panel B: Correlation matrix of all the variables

Variables	Std. beta	Diff beta	Jump beta	Firms size	Profitability	Leverage	Capital ratio
Std. beta	1						
Diffu beta	0.80	1					
Jump beta	0.67	0.38	1				
Firms size	0.56	0.56	0.26	1			
Profitability	0.08	0.04	0.08	-0.04	1		
Leverage	0.20	0.23	0.10	0.38	-0.24	1	
Capital ratio	0.01	0.02	0.01	-0.02	0.06	0.02	1

Table 2.7 reports the results from regression analysis. The first three columns of results consider the role firm characteristics in the behavior of the diffusion beta and the final three columns for the jump beta. The first two columns explore subsets of the explanatory variables, with leverage included (excluded) in column 1(2) and the capital ratio excluded (included). It is clear from a comparison of columns 1-3 that in the continuous case when both leverage and capital ratio are included neither have a significant effect, but when they are included individually they do so. This is not the case for the jump betas.

The preferred results of column (3) in each case reveal that diffusion beta is positive affected by both firm size and profitability, as anticipated. The effects of leverage (positive) and bank capital (negative) are insignificant. Jump beta is also affected by firm size and profitability, but additionally a significant positive effect from leverage, while the capital ratio is insignificant.

The results support that larger Japanese banks are more sensitive to market movements than smaller institutions, regardless of whether they occur through a jump or not. However, the effect of size is larger for the jump beta than diffusion beta, implying that large banks react more to information transmitted by abrupt changes even more than they do to continuous changes. The result is consistent with previous studies particularly for US bank holding companies and European banks (e.g. (Saunders et al. 1990,Anderson and Fraser 2000, Haq and Heaney 2012).

Table 2.7: Betas and firm characteristics

	$\hat{\beta}^c$			$\hat{\beta}^j$		
Variables	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Firm Size	0.321***	0.312***	0.318***	0.421***	0.363***	0.421***
	(0.023)	(0.022)	(0.024)	(0.044)	(0.040)	(0.045)
Profitability	0.002***	0.002***	0.002***	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	0.008*		0.004	0.033***		0.034***
	(0.004)		(0.006)	(0.010)		(0.011)
Capital ratio		-0.006**	-0.004		-0.006	-0.001
		(0.003)	(0.003)		(0.004)	(0.005)
Constant	-3.311***	-2.439***	-2.876***	-6.156***	-2.480***	-6.219***
	(0.540)	(0.175)	(0.655)	(1.135)	(0.330)	(1.296)
N	6450	6450	6450	5194	5194	5194
Chi-squared	4053.5	4056.7	4056.5	1089.7	1077.4	1087.2
R-squared	**0.49**	**0.48**	**0.49**	**0.21**	**0.20**	**0.21**

Note: The sample consists of 6522 observations from 47 banks in Japan, available from Thompson DataStream database from 2001-2012. *Firm Size*= natural log of market capitalization. *Profitability*= Earnings before interest, taxes, depreciation & amortization /Total assets. *Leverage Ratio*= Total debt over total assets. *Capital Ratio*= book value of equity divided by total assets. All firm characteristics data are obtained from the DataStream database. *Time dummies* are a dummy variable that accounts for the year fixed effects (FE). **Standard errors** are displayed in parentheses below the **coefficients**. Time dummies are included but not shown. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% level, respectively. The baseline econometric model is:

$$\boldsymbol{\beta_{i,t} = \gamma_1 Firm\ size_{i,t} + \gamma_2 Profitability_{i,t} + \gamma_3 Leverage_{i,t} + \gamma_4 capital\ ratio_{i,t} + time\ dummies_{i,t} + \varepsilon_{i,t}}$$

Profitable banks are more sensitive to both diffusion and jump systematic risk than their less profitable counterparts, supporting the hypothesized positive risk-return relationship. A decrease of one percentage point in the profitability ration is estimated to lead to decrease of 0.002 in the diffusion beta, assessed at the mean value of profitability, this is equivalent to a decrease in the profitability ratios for Japanese banks from 12% to 11% resulting in a decrease in diffusion beta of 0.002. It immediately apparent that a large change in profitability would be required to alter beta to economically meaningful extent. However, in this case the impact of continuous movements is slightly more impactful than jump movement; that is the effect for profitable banks is not importantly different if the information arrival through price arrives abruptly or continuously. A possible reason is that profitable banks often employ aggressive business strategies and consequently exhibit higher risk. Borde et al. (1994) reach the same conclusion for US insurance companies.

While leverage is not statistically significant in determining diffusion beta, it has a positive effect on jump beta. The results reveal that financial firms with higher leverage (debt capital) are more responsive to jumps in the market. As higher leverage ratios make financial firms riskier, these highly leveraged firms are more sensitive to market jumps. Information arrival through abrupt price movements may cause banks to adjust their business behavior, whereas planning should have eliminated this channel in relation to the known continuous price process.

To gain some sense of the economic relevance of these results we calculate that an increase in bank size by 1 percentage point (assessed at the mean) is associated with a 0.32 percentage point increase in diffusion beta and 0.42 percentage point increase in jump beta. An increase in profitability and leverage by 1 percentage point would increase bank diffusion systematic risk by a mere 0.001 point and 0.008 point respectively, while the jump beta effects are for increases by 0.001 point and 0.034 point respectively. Bank size is clearly the largest economic effect in our firm characteristic set.

The recent global financial crisis (GFC) is an exogenous shock to a firm's investment choices and thus it provides an opportunity to understand the relative importance of these determinates of bank systematic risk and jump risk and how these factor evolved with the changes in world economy during the crisis period. Yamori et al. (2013) suggest that Japanese experience with their economic collapse in the 1990s enhanced the ability of the financial system to respond; through programs implemented including deferrals for interest rate and principal payments and the extension of further loans. The government also introduced support measures which partly explain the willingness of banks to extend credit, applying guarantee measures which absorbed their risk of loss, and loosening capital adequacy requirements. Whilst the drop in business conditions reported from Tankan was severe, the contraction of credit conditions was much less so; see Yamori et al. (2013).

Although no major failures took place in the Japanese financial industry during the GFC period Miyakoshi et al. (2014) find evidence of the transmission of risk from the manufacturing industry to the financial industry, observing that the Japanese exporting industry, including the Toyota, Honda, and Nissan motor vehicle companies, suffered extraordinary deficits in the two fiscal years following the crisis. To characterize the betas and to aid our discussion, we split the sample period into crisis (July 2007 to May 2009) and the non-crisis period.[23]

[23] We use the crisis period identified in Dungey and Gajurel (2014).

The following model is used to explore the impact of the financial crisis on the relationship between different betas and its determinants:

$$\beta_{i,t} = \alpha_0 + \sum_{i=1}^{m} \gamma X_{i,t} + \sum_{i=1}^{m} \gamma_{1_t} X_{i,t} + \sum_{i=1}^{m} \gamma_{2_t} D_t X_{i,t} + \sum \theta_t\,(time\ dummies) + \mu_{i,t} \quad (2.21)$$

where we introduce a GFC dummy D_t= 1 for the crisis period July 2007- May 2009.

Table 2.8 reports the results of the impact of the GFC on the relationship between the betas and firm characteristics. Focusing on column (3) for each of the beta regressions in Table 2.8 shows that the effects of firm size, profitability and leverage reported in Table 2.7 are retained – diffusion beta is positively related to firm size and profitability, and jump beta is positively related to firm size, profitability and leverage.

In relation to how the GFC affected the association between different betas and bank characteristics variables, we observe some interesting results from the multiplicative terms. The estimated coefficients on Profitability*GFC dummy is positive and statistically significant. This suggests that the impact of profitability on diffusion beta increased during the GFC period.

There are two important further results. For diffusion beta, there is a significant addition to the impact of profitability on beta during the crisis period. In the crisis period the impact of profitability is increased by almost 60 percent, more profitable firms reflected more of the market movements (or perhaps in the context of the environment, the market was strongly associated with the loss of profitability of the banking sector). The jump beta, however, does not show any change in its relationship with profitability between the non-crisis and crisis periods. Rather, it has a dramatic increase (almost doubling) of the impact of leverage. During the crisis period being more leveraged resulted in a greater beta in response to abrupt price movements. There is also a statistically significant shift in the intercept term for the jump beta, supporting a more negative intercept during the crisis than non-crisis periods. Banks with larger debt obligations (relative to equity) are more sensitive to market fluctuations during financial distress. It is not surprising that banks with low debt are seen as attractive during volatile times and become safe havens for investors.

Overall, the results show that the four firm characteristic variables significantly influence not only diffusion systematic risk but also jump risk of banks.

Table 2.8: Betas and firm characteristics (the impact of GFC period)

	$\widehat{\beta}^c$			$\widehat{\beta}^j$		
Variables	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Firm Size	0.320***	0.313***	0.313***	0.426***	0.374***	0.443***
	(0.023)	(0.022)	(0.024)	(0.043)	(0.039)	(0.041)
Profitability	0.001***	0.001***	0.001***	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Leverage	0.007		0.003	0.029***		0.028***
	(0.005)		(0.006)	(0.010)		(0.011)
Capital ratio		-0.005*	-0.004		-0.006	-0.003
		(0.003)	(0.003)		(0.004)	(0.004)
Profitability*GFC dummy	0.001**	0.001**	0.001**	-0.0001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Leverage*GFC dummy	-0.005		-0.007	0.029		0.044**
	(0.005)		(0.006)	(0.019)		(0.021)
Capitalratio*GFC dummy		-0.001	-0.002		0.005	0.014
		(0.002)	(0.002)		(0.008)	(0.009)
GFC dummy	0.575	0.085***	0.740	-2.748	0.022	-4.159**
	(0.511)	(0.018)	(0.572)	(1.808)	(0.064)	(2.021)
constant	-3.211***	-2.450***	-2.701***	-5.825***	-2.573***	-5.872***
	(0.544)	(0.175)	(0.663)	(1.131)	(0.316)	(1.198)
N	6450	6450	6450	5194	5194	5194
Chi-squared	4155.3	4157.9	4153.4	1100.0	1092.5	1128.6
R-squared	**0.49**	**0.49**	**0.49**	**0.21**	**0.20**	**0.21**

Note: This table represents the impact of the financial crisis on the relation between different betas and their determinants. D_t= GFC dummy equals 1 for crisis period if the year is July 2007- May 2009 and otherwise zero to account for non-crisis period; $D_t \times X_{i,t}$ = interaction term between GFC dummy (D_t) and each bank-specific variable $X_{i,t}$ (i.e. firm size, profitability, debt leverage, and capital ratio). *Time dummies are* a dummy variable that accounts for the year fixed effects (FE). **Standard errors** are displayed in parentheses below the **coefficients**. Time dummies are included but not shown. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

2.6. The risk-return relationship

Theoretically, Merton (1976) assumes stock jump risk is diversifiable, while papers such as Santa-Clara and Yan (2010) assume market jump risk is priced. We consider whether jump risks are priced cross-sectionally. The conventional CAPM implies that securities have same expected returns if they have same betas. The expected risk-return relationship of the jump-diffusion model is different. The jump-diffusion model has two different types of betas instead one. One measures the systematic risk when no jump occurs, and the other measures the systematic risk when jump occur. Different securities have different diffusion and jump beta risks. Hence, securities will have different expected returns even if they have the same diffusion betas.

The conventional CAPM implies two-fund separation which claims that all investors hold the same portfolios, a market portfolio and a riskless asset. This is no longer true in the jump-diffusion model because investors may have different preferences to diffusion and jump betas. It would be difficult, if not impossible, to find a portfolio that is optimally invested and which has the same premium for both the diffusion and jump risks of its component securities.

The importance of these risks is now a fundamental premise of the option pricing literature and those studies have argued that the risk premia associated with jump risks are different from the premia associated with diffusion risks (see, e.g., Eraker (2004); Pan (2002); Todorov (2009) and references therein). This motivates our test of whether the two types of betas carry separate risk premia. It is especially important to determine the contribution of jumps to periods of market stress because jump risk, either in returns or in volatility, cannot typically be hedged away, and investors may demand a large premia to carry these risk; for instance, Pan (2002). We focus on the contemporaneous relationships between realized factor loadings and realized stock returns, as in (Ang et al. 2006), and others.

The test assets we use in our pricing regressions are individual stocks rather than portfolios. Ang et al. (2010) show that constructing portfolios ignores important information (especially, as stocks within particular portfolios have different betas) and leads to larger standard errors in cross-sectional data. In our empirical analysis, we choose panel regression with both period and cross-section fixed effects over the conventional Fama and MacBeth (1973) cross-sectional regressions. Although Fama and Macbeth (FM) regression is a standard methodology to validate an asset pricing model, Petersen (2009) and Pasquariello (1999) indicate that FM two step procedures do not properly explain estimation errors and lack independence between cross-sectional errors. Therefore, we focus on individual stocks rather than portfolios, estimating panel regressions using all stocks in our sample as follows:

$$\bar{r}_{i,t} = \alpha_0 + \gamma_c \widehat{\beta^c_{i,t}} + \gamma_j \widehat{\beta^J_{i,t}} + \emptyset SIZE_{i,t} + \theta BM_{i,t} + \varepsilon_{i,t} \tag{2.22}$$

where $\bar{r}_{i,t}$ is the realized excess return on stock i the t-th month. We use the average monthly return as a proxy for realized excess returns, as there are no risk-free rates in Japan comparable to U.S. Treasury bill rates.[24] $\beta^s_{i,t}$ $\beta^c_{i,t}$, $\beta^j_{i,t}$ are the standard beta, the diffusion beta, and the jump beta of firm i at month t, from our estimates in section 2.2.2. For comparison, we also estimate

[24] Alexeev et al. (2017) also use the average monthly return as a proxy for realized excess returns in order to extract the risk premia.

similar regressions by replacing the two betas by the standard CAPM beta, $\beta_{i,t}^{s}$. Based on these panel regressions equations, with fixed effects in both the cross-section (firms) and period (time) dimensions, we then estimate the risk premiums associated with the different betas and explanatory variables.

Table 2.9 presents the unconditional regression results for the stock returns and each of the three betas ignoring the possible conditional beta/return relationship. The first three models show results for univariate regressions of returns on each beta. In model (4) of Table 2.9, we examine the effect of including both the diffusion and jump beta estimates without considering the influence of size and BM effects. Model (5) in Table 2.9 examine the effect of including both the diffusion and jump beta estimates after controlling for size and BM effects.

The parameter loadings on the standard beta, the diffusion beta, and the jump beta in models (1) to (3) of Table 2.9 are all positive and significant, consistent with CAPM theory. Model (4) in Table 2.9 shows that the diffusion beta becomes insignificant when controlling for jump beta. However, the effect of jump beta remains significant even after controlling the effect of diffusion beta. From Table 2.9, it can be observed that, even in combination with variable size and BM, the significantly relationship between average returns and jump beta still persists in all bivariate regressions. This implies that stocks with high sensitivities to jump risk can expect higher returns, that is, jump risks carry a positive market price for risk.

2.6.1 Diffusion and jump risk in up and down markets

The unconditional results are consistent with existing asset pricing tests in a broad setting. However, we claim that the unconditional specification above is not appropriate for determining whether there is actually any relation between betas and returns. Since excess returns may behave differently in up and down markets, the results above may not be reliable as they do not account for the effects of up and down markets. In view of this, we now consider the up and down market risk-return model.[25]

[25] For instance, Pettengill et al. (1995) find a positive (negative) relationship between beta and return by taking into account whether the excess market return is positive (up market) or negative (down market) in the US markets. Following Pettengill et al. (1995), Faff (2001), Lam (2001), Elsas et al. (2003), and Hung et al. (2004), studying the Australia, Hong Kong, German and UK markets, respectively, all find a significant beta-return relationship. Using cross-sectional regression method, Hodoshima et al. (2000) find, on the Japanese market, that taking into account positive and negative market excess returns produces a significant relationship between stock returns and beta in Japanese market.

Table 2.9: Unconditional risk-return trade-off for individual banks

	Model				
Risk Premia	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Standard Beta	0.007*				
	(0.004)				
Diffusion Beta		0.007*		0.006	0.005
		(0.004)		(0.004)	(0.004)
Jump Beta			0.003*	0.003*	0.003*
			(0.001)	(0.002)	(0.002)
Size					0.708
					(1.08)
BM					0.028***
					(0.007)
Constant	-0.009***	-0.008***	-0.009***	-0.009***	-0.088
	(0.002)	(0.002)	(0.002)	(0.002)	(0.131)
R-squared	**0.04**	**0.04**	**0.04**	**0.04**	**0.04**

Note: Unconditional panel regressions of monthly stock returns without splitting markets into up and downs for individual stocks, rather on stock market betas (Beta), Size (in natural logarithm) and BM (in natural logarithm) over the whole sample period. The sample consists of 47 banks in Japan that are constituents of Nikki 225 index over the period 2001-2012. Clustered **Standard errors** are displayed in parentheses below the **coefficients**. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Bollerslev et al. (2015) find that the risk premium associated with jump beta is statistically significant, while the diffusion beta does not appear to be priced in the cross-section. The decompositions of Todorov and Bollerslev (2010) and Bollerslev et al. (2015) do not make a distinction between upside market and downside market risk. The arguments based on asymmetric preferences by investors are, however, equally applicable in a context where we disentangle diffusion risk and jump risk. In particular, given the pricing results of Bollerslev et al. (2015), it is unclear whether down market risk is priced higher than up market risk. In particular, we test for the price diffusion risk and jump risk between different market states. We examine this for two reasons. First, information on the states of any asset market is relevant for investors. Investors who may follow a market timing strategy can obtain a long position under a bull (up) market and a neutral or short position under a bear (down) market. Investors who do not engage in market timing strategies may incorporate the different behavior of asset returns in their risk management (Perez - Quiros and Timmermann 2000). Further, up and down markets can affect asset pricing, as they are an important source of time variation in risk premia (see, for example Ang et al. (2006)).

To examine the relationship between beta and realized returns, conditioning on the sign of market return, testing is modified by including a dummy variable in the panel regression Equation. (2.22), thus allowing of positive and negative market returns to be separated out. This is in accordance with the methodology of Pettengill et al. (1995). This is shown as follows:

$$\bar{r}_{i,t} = \alpha_0 + \gamma_{c\,up}\,\delta.\widehat{\beta^{c}_{i,t}} + \gamma_{c\,down}\,(1-\delta).\widehat{\beta^{c}_{i,t}} + \gamma_{jup}\delta.\widehat{\beta^{J}_{i,t}} + \gamma_{jdown}(1-\delta).\widehat{\beta^{J}_{i,t}} + \sum_{n=1}^{p}\left[\emptyset_{up}\,\delta.X_{i,t} + \emptyset_{down}\,(1-\delta).X_{i,t}\right] + \varepsilon_{i,t} \tag{2.23}$$

where δ =1 if $r_{mt} > 0$ (an up market) and δ =0 if $r_{mt} < 0$ (a down market). In this study, we include diffusion beta, jump beta, standard beta as well two firm-specific explanatory variables: firm size (SIZE) and book-to-market ratio (BM). Incorporating a dummy variable into the regression allows for the existence of a negative realized market risk premium. We expect $\alpha_{i,t} = 0$ and $\gamma_{c\,up}$ ($\gamma_{c\,down}$) to be positive (negative) and statistically significant, implying the significance of beta as a risk measure. Monthly estimates $\gamma_{c\,up}$ are averaged from ($\overline{\gamma_{c\,up}}$) from which the following hypotheses are tested: H_o: $\overline{\gamma_{c\,up}} = 0$ against the alternative H_o: $\overline{\gamma_{c\,up}} > 0$, and $H_o : \overline{\gamma_{c\,down}} = 0$ against the alternative $H_o : \overline{\gamma_{c\,down}} < 0$.

Table 2.10 presents our baseline results. In an ex post context, Model (1) in Table 2.10 shows a significant positive (negative) relationship between standard beta and return during up and (down) markets. When we decompose the CAPM beta into a diffusion beta and jump betas in up and down markets as in model (2) to (4) we see that both the betas carry a significant premium at the 1% level. The result also show that the jump beta carries the larger premium of the two in both up and down market. The null hypothesis of no beta–return relations ($H_o : \gamma_{c\,up} = 0$ and $H_o : \gamma_{c\,down} = 0$) is clearly rejected. Using the results in Table 2.10 for our preferred model (5), a 2-standrad-deviation difference in jump beta during the whole sample period, for the 5-min sampling frequency will lead to a difference in expected return of 2*0.6404* 0.6%*12 = 9.22% and 2*0.6404* 0.6%*12 = 9.22% per year, respectively for the up and down markets, which are large and economically meaningful difference in expected return. These are very close to estimates in Bollerslev et al. (2015) in the US market. This supports the argument that when the market is doing well the higher risk firms, as measured by the two betas, have greater returns than less risky firms. On the other hand, higher risk firms do worse than less risky firms when the market is overall is doing poorly. This finding is constant with Pettengill et al. (1995); Hur et al. (2014); Morelli (2011); Cotter et al. (2015); Hodoshima et al. (2000) in the US, the UK and the Japanese markets, respectively.

This study also consider the effect of size and BM on the relation between betas and returns when markets are segmented into up and down and markets. We find that diffusion and jump beta remain significant even after controlling for size and BM effects in up and down markets. The improvements in the adjusted-R^2 statistics as compared to the 2-beta model support the modelling of the up and down market conditional relationships.

Observing the relationship between size and returns, size is virtually not priced at all during up market and is priced negatively during down markets. The observe results argues against the distress risk explanation between the beta and size relationship. A number of authors have suggested that the size premium represents payment for some sort of distress risk. Campbell and Vuolteenaho (2004) suggest that the payment to small firms represents payment for a greater sensitivity to cash flow risk. Other authors (see for example Chan et al. (1985) and Vassalou and Xing (2004)) have suggested that the size premium may exist because small firms have greater default risk than large firms. Likewise, Chan and Chen (1991) argue that many small-firm securities are "fallen angels" that have declined in market value because of adverse market conditions and face the possibility of further distress. To the extent that small-firm securities do attract a premium for some form of distress or default risk, a relationship between the size effect and market conditions is clearly suggested. If small-firm securities attract a premium for distress risk, this premium ought to be realized when investors are generally optimistic. In market states where investors are pessimistic, firms with higher distress risk should experience low returns as investors re-value these securities downward to compensate for high default risk. Thus, in down markets small-firm securities should perform poorly relative to large-firm securities, but in up-markets investors in small-firm securities is rewarded for holding distress or default risk.

The hypothesis that a size effect resulting from payment to risk should be paid in up markets is consistent with arguments made by Lakonishok et al. (1994). They argue that value stocks ought to underperform glamor stocks in adverse market conditions if the value premium results from compensation for risk. This follows because in adverse market conditions high-risk value stocks ought to be unattractive to risk-averse investors. Further support for the hypothesis that a distress risk premium should be paid to size in up markets rather than in down markets is provided by Perez‐Quiros and Timmermann (2000). They argue that small firms rapidly lose asset value in recessions; therefore small firms should experience greater losses than large firms in bear market periods associated with economic recessions. Thus the size premium, if paid for distress risk, ought to be paid in up markets.

As reported in Table 2.10, statistics revealed size is virtually not priced at all during up markets and is priced negatively, with a monthly premium of 0.35%, during down markets. There is no relationship between size and returns in up markets after considering the role of beta. Contrary to the distress risk explanation of the size effect, the relationship between size and returns comes entirely from down markets. The observed results appear to contradict the generally hypothesized pricing relations. Our results are inconsistent with Campbell and Vuolteenaho (2004), Chan et al. (1985), Vassalou and Xing (2004), and Chan and Chen (1991) arguments that the payment to small firms represents payment for a greater sensitivity to cash flow risk and greater default risk or these firms are more likely to get adversely affected in bad market states. Therefore our findings indicate that 'relative distress' argument used in Fama and French (1996) to justify risk adjustment using factor loadings on SMB portfolios can be questioned.

It is plausible however that if small firms do face higher financial distress cost, they may optimally structure themselves (e.g. through financial leverage or other operating decisions) to insulate themselves against bad states of the world. Under those circumstances the stock returns may behave as we find here even though other aspects of financial performance may be more affected by bad times. This explanation is consistent with George and Hwang (2010) argument for distress risk and leverage puzzle in stock returns. Another explanation is that, the unique risk characteristics of firms in Japanese market may imply the existence of a significant negative size effect in down markets. To the extent that size reflects diversification of activities, liquidity, timeliness and quality of corporate information disclosure, and the level of transactions costs involved, larger firms tend to have lower non-market risk. However, a special feature of the Japanese market is that, unlike the US market, most large firms are in the finance and real estate property sectors, which are exposed heavily to systematic risk factors on an international scale, such as interest rate risk, inflation risk, and political uncertainties, whereas most small firms are engaged in trading or manufacturing business which is less vulnerable to market risk. So, large firms possess large betas and small firms possess small betas. This gives rise to a positive correlation between size and beta (See, Table 2.6). In sum, it may be generalized that large firms in Japanese market have large total risk (large market risk plus small non-market risk) and small firms have small total risk (small market risk plus large non-market risk). This helps explain the positive (negative) size effect during up (down) markets. Thus, in the Japanese market, it may be argued that size also proxies for risk but with a pricing effect reverse to that generally suggested by theory and evidence.

With respect to BM, a statistically significant negative relationship is found during the down markets, consistent with Pettengill et al. (2002). The results suggest that in good times, when the market returns are up, the market is less worried about bankruptcy. However, in bad times when the market returns are down, the market is more concerned about bankruptcy; distressed companies with high BM ratios will suffer low returns (security prices decrease) as the distressed risk is priced back into the security. Such an explanation implies a negative BM pricing effect during down markets.

Overall, our findings provide strong evidence that high-risk stocks outperform low-risk stock markets when the realized world market is positive and similarly the high-risk stock markets incur higher losses when the realized world market return is negative.

2.6.2 Extensions

This section describes several extensions of basic analysis in section 3.6.1. To check the robustness of our empirical findings, following Wu and Lee (2015), we first extend the Equation (2.23) to a model with regime dependent constant term: $\alpha_{i,t} = \alpha_{1,t}$ for up market and $\alpha_{i,t} = \alpha_{2,t}$ for down market. The empirical results are reported in Table 2.11.

The estimates of $\alpha_{1,t}$ and $\alpha_{2,t}$ are now significantly positive and significantly negative, respectively, which captures the positive mean excess return in the up market and the negative mean excess return in down market. As for the coefficients for continues beta and jump beta are qualitatively similar to those with a time-invariant constant term reported in Table 2.10.

As Lanne and Saikkonen (2006) point out the presence of a constant term renders conditional mean estimation very inaccurate when the constant term estimates appears to be significant, we therefore employ the restriction $\alpha_{i,t} = 0$ to address this estimation problem. As shown in Table 2.11, the estimated coefficients are qualitatively similar those reported in Table 2.10.

Table 2.10: Risk-return trade-off for individual banks during up and down markets

	Model				
Risk Premia	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	Up Market				
Standard Beta	0.077***				
	(0.004)				
Diffusion Beta		0.089***		0.028***	0.015***
		(0.005)		(0.004)	(0.004)
Jump Beta			0.040***	0.033***	0.006***
			(0.003)	(0.003)	(0.002)
Size					0.328
					(0.207)
BM					-0.002
					(0.005)
	Down Market				
Standard Beta	-0.086***				
	(0.004)				
Diffusion Beta		-0.102***		-0.024***	-0.016***
		(0.005)		(0.006)	(0.006)
Jump Beta			-0.045***	-0.039***	-0.006**
			(0.004)	(0.004)	(0.003)
Size					-0.350*
					(0.200)
BM					-0.017***
					(0.002)
Cons	0.001	0.002	0.001	0.001	0.004
	(0.001)	(0.001)	(0.003)	(0.003)	(0.025)
R-squared	**0.45**	**0.29**	**0.43**	**0.44**	**0.57**

Note: Pooled regressions of monthly stock returns in up and down markets for individual stocks on just their stock market betas (Beta) over the whole sample period. The sample consists of 47 banks in Japan that are constituents of the Nikki 225 index over the period 2001-2012. Clustered **Standard errors** are displayed in parentheses below the **coefficients**. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

The existing literature indicates that risk factors such as conditional volatility (Lundblad 2007) or implied volatility (Connolly et al. 2005) are elevated during recessions. Investors also tend to avoid risky assets and behave differently under extreme market conditions. Thus we investigate whether extreme market movements, such as a financial crisis, could alter the parametric estimates of the risk-return relationship. We re-estimate our jump-diffusion model under the pre-crisis and post-crisis, crisis and post-crisis periods and show how the risk-return relationship varies under different economic conditions. Each of the three sub periods describes a different episode of the stock market. We again concentrate on up and down markets.

Table 2.11: Risk-return trade-off for individual banks during up and down markets with a regime dependent constant term

	Monthly Return	
Risk Premia	**Constant#0**	**Constant=0**
	Up Market	
Diffusion Beta	0.013***	0.029***
	(0.004)	(0.005)
Jump Beta	0.005**	0.034***
	(0.002)	(0.002)
Constant	0.045***	-
	(0.002)	
	Down Market	
Diffusion Beta	-0.006	-0.024***
	(0.005)	(0.006)
Jump Beta	-0.008***	-0.038***
	(0.002)	(0.003)
Constant	-0.046***	-
	(0.003)	
R-Squared	**0.56**	**0.44**

Note: Premia estimates and their standard errors as in Table 2, but for different constant terms. Clustered **Standard errors** are displayed in parentheses below the **coefficients**. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Table 2.12: Risk-return trade-off for individual banks during up and down markets: sub sample analysis

	Sample Periods		
Risk Premia	**Pre-crisis Period**	**Crisis Period**	**Post-Crisis Period**
	Up Market		
Diffusion Beta	0.035***	0.057***	0.006
	(0.007)	(0.008)	(0.005)
Jump Beta	0.040***	0.016***	0.046***
	(0.004)	(0.005)	(0.005)
	Down Market		
Diffusion Beta	-0.023***	-0.046***	-0.008
	(0.007)	(0.013)	(0.010)
Jump Beta	-0.038***	-0.022**	-0.041***
	(0.004)	(0.009)	(0.006)
Constant	0.001	-0.004	-0.009*
	(0.002)	(0.006)	(0.005)
R-Squared	**0.41**	**0.45**	**0.52**

Note: Premia estimates and their standard errors as in Table 2, but for different subsamples. Clustered **Standard errors** are displayed in parentheses below the **coefficients**. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Table 2.13: Test of symmetry hypothesis

Panel A				
	Full Sample period	**Pre-crisis**	**Crisis**	**Post-crisis**
	t-statistic			
$\gamma_{c\,up} - \gamma_{c\,down} = 0$	0.37	1.13	0.51	0.04
$\gamma_{j\,up} - \gamma_{j\,down} = 0$	0.61	0.08	0.24	0.20
Panel B				
	Full Sample period	**Pre-crisis**	**Crisis**	**Post-crisis**
	t-statistic			
$\gamma_{c\,up} - \gamma_{j\,up} = 0$	0.50	0.22	15.64***	23.46***
$\gamma_{c\,down} - \gamma_{jdown} = 0$	2.74*	1.75	1.37	5.17**

Note: The table report the t-statistic for testing the symmetry hypothesis between the risk premia $\gamma_{c\,up}$ $and\ \gamma_{j\,down}$ in up and down markets. Results are for the full testing period as well as sub sample periods. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Table 2.14: Risk-return trade-off for size-sorted stock portfolios during up and down markets

	Size Sorted Portfolios (Qunitiles)				
Premia	**Small**	**2**	**3**	**4**	**Large**
	Up Market				
Diffusion Beta	0.031***	0.022**	0.0320***	0.065***	0.054***
	(0.007)	(0.010)	(0.012)	(0.017)	(0.017)
Jump Beta	0.019***	0.039***	0.026***	0.034***	0.046***
	(0.006)	(0.007)	(0.005)	(0.007)	(0.008)
	Down Market				
Diffusion Beta	-0.049***	-0.021**	-0.033**	-0.065***	-0.050**
	(0.008)	(0.010)	(0.015)	(0.016)	(0.024)
Jump Beta	-0.028***	-0.035***	-0.045***	-0.032***	-0.042***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.013)
Constant	0.012**	-0.003	0.011***	0.003	0.007
	(0.005)	(0.005)	(0.004)	(0.004)	(0.007)

Note: Estimates of the risk prices from pooled OLS regression using size sorted portfolios, rebalanced each year. **Standard errors** are displayed in parentheses below the **coefficients**. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Table 2.12 presents the results. In the pre-crisis period, exposures to diffusion and jump risks are rewarded with returns during up markets, and are penalized with losses during down markets. In transitioning from the pre-crisis to the crisis period, we find that both the premium and discount for diffusion beta increase whereas both the premium and discount for the jump beta decrease in the crisis period. By contrast, both the premium and discount for the diffusion and jump beta show opposite results in transitioning from the crisis to the post-crisis period. In the pre-crisis (or stable) period both the betas are priced significantly, with the jump premium larger than the diffusion premium. Large surprises are priced higher than small surprises. In the crisis (or unstable) period both the betas are still significantly priced but the diffusion premium is now larger than the jump premium. Small surprises are priced higher than large surprises. In the post-crisis (or recovery) period only the jump risk is priced significantly. Any large good news is rewarded largely and any further large bad news is penalized heavily.

Table 2.15: Fama-Macbeth cross-sectional regressions

	Model				
Risk Premia	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	Up Market				
Standard Beta	0.025				
	(0.058)				
Diffusion Beta		0.004		0.002	0.025
		(0.086)		(0.020)	(0.026)
Jump Beta			0.037***	0.031***	-0.006
			(0.005)	(0.006)	(0.021)
Size					-0.006
					(0.219)
BM					-0.001
					(0.006)
	Down Market				
Standard Beta	-0.093***				
	(0.008)				
Diffusion Beta		-0.091***		-0.019	-0.067*
		(0.024)		(0.012)	(0.037)
Jump Beta			0.046***	-0.045***	-0.011
			(0.005)	(0.007)	(0.016)
Size					-0.377*
					(0.225)
BM					-0.017
					(0.017)
Constant	0.002	0.002	0.001	0.001	0.035
	(0.004)	(0.004)	(0.004)	(0.004)	(0.029)
R-squared	**0.40**	**0.29**	**0.39**	**0.45**	**0.55**

Note: Cross-sectional pricing of jump and continues risk in up and down markets. Sample period is from January 2001 to December 2012. We run Fama–MacBeth regressions of 12-month excess returns on contemporaneous realized betas. Observations are at monthly frequency and we adjust standard errors accordingly using 2 Newey–West lags. Standard errors are displayed in parentheses below the coefficients. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Given the above relationship found between betas and returns, we test the symmetrical relationship between betas and returns during up and down markets over the full sample and the three periods to compare the relative magnitudes of the different premia for both the diffusion and jump betas. A two population t-test is used to test the symmetrical relationship between the mean of estimated up market risk premia and the estimated down market risk premia from the Equation, (2.24). The results of a two-population t-test, as reported in Panel A of Table 2.13 clearly do not reject the null hypothesis of symmetry over the total testing period, and the three sub periods with the exception of the pre-crisis period (only at the 10% significance level). We can safely say that the absolute values of the premiums for both the diffusion and jump risks are generally symmetrical for up and down markets. The result provides significance evidence to support the symmetrical relationship between betas and return during up and down markets. This is supportive to Pettengill et al. (1995) who found a symmetrical relationship are in US security returns.

In addition, since the risk premia associated with discontinuous, or jump, risks often appear to be quite different from the premia associated with diffusion risks, we examine whether the risk premia associated with diffusion and jump risk are of equal magnitude and symmetrical relationship exists between them during up and down markets by testing the equality of pairs of the regression coefficients ($\gamma_{c\ up}$ *and* $\gamma_{j\ up}$; $\gamma_{c\ down}$ *and* $\gamma_{j\ down}$) as shown in Panel B of Table 2.13. Comparing the relative magnitudes of the different premiums, we see that the symmetrical relationship only exists in the up markets of the total sample and the pre-crisis sub-sample periods. However, the estimated risk premiums for diffusion risk and jump risk reject symmetry for the down markets of all periods and the up markets of the crisis and post-crisis periods. We also notice (in conjunction with Table 2.12) that for the crisis period the diffusion component for up markets are the dominant pricing ingredients whereas for the post-crisis period the jump component is the dominant factor. During the crisis period, we do not expect positive jumps and consequently the market does not have a premium for positive jumps. In post-crisis, the market compensates by having a higher premium for positive jumps (i.e. expecting a fast recovery), and at the same time having a higher discount for the negative jumps as still remember the recent past crisis. For the pre-crisis period, we do not observe a clear difference between the estimated risk premiums for diffusion and jump risks during up markets and down markets.

For our robustness checks, we use the size sorted portfolio analysis to see whether our base line results remain valid; see Table 2.14. Our results indicate that when compared with low-beta portfolios, high-beta portfolios earn higher returns in up markets and incur losses in down markets. For comparability with previous studies, we also use Fama–MacBeth regressions to estimate model (3) of Table 2.10. We present the regression results in Table 2.15. Our base line results remain robust. The results are consistent with Bollerslev et al. (2015) who observed a positive relation between a stock's return and its jump beta for all stocks that are constituents in the S&P 500 index over 1993-2010. That is, the jump beta may have a different price of risk than the diffusion beta. The results are broadly consistent with Schuermann and Stiroh (2006) and Viale et al. (2009) who provide evidence on the risk factors priced in bank equities. Schuermann and Stiroh (2006) examine the weekly returns for the U.S. banks form 1997-2005 and show that the market risk factor dominates in explaining bank returns, followed by the Fama-French factors. Viale et al. (2009) identify common risk factors in US banks stocks from 1986-2003 applying CAPM, Fama-French factors , and ICAPM and find that market factor are significant explanators of the cross section of bank stock returns.

The results support the initial hypothesis of this paper that jump beta is larger than that of diffusion beta, in line with the approach of Patton and Verardo (2012) emphasizing that the role of learning in disseminating information to the market is supported by higher beta around information rich events (such as jumps). Further, our panel results show that the jump betas convey more information than the diffusion beta in the explanation of average returns, supporting the importance of separating jump and diffusion beta in assessing risk premia.

2.7. Conclusions

Jumps are infrequent but large changes in stock prices potentially driven by significant information shocks. Detecting jumps and studying their dynamics is important because of the consequences in applications including asset pricing and risk management. As jump risk, either as large negative returns or as high volatility cannot typically be hedged away, and investors may demand a large premium to carry jump risk.

In this paper, we identify jumps in the Japanese banking sector, which is well known as a bank-centered financial system. Using high-frequency price data for 50 commercial banks in the Nikkei 225 index over the period 2001-2012, we find 272 jump days out of 2866 trading days, corresponding to 115 months out of 144 months. We use an extension of CAPM to relate a stock's return to two types of systematic risk exposures as measured by two types of beta: the diffusion beta and the jump beta. The diffusion beta is associated with the stock's sensitivity to a market continuous movement while, jump beta is associated with the stock's sensitivity to a market discontinuous movement.

Jump betas are consistently larger than the diffusion betas in our empirical results, and firm fundamentals play important roles in determining firm's cost of capital in the 2-beta model. We find that large banks are more sensitive to jumps than the small banks and high leverage stocks are more exposed to market jumps. Profitable firms are sensitive to both continuous and jump market moves. We introduce and test a new 4-beta CAPM model by combining the diffusion and jump betas of Todorov and Bollerslev (2010) and the conditional betas of Pettengill et al. (1995), into a single model to detect any asymmetries in response. A distinguishing feature of our approach is that we allow for a conditional relationship between beta risk and premiums in our tests. In a separate investigation of up and down markets, we find that both the diffusion and the jump beta are significantly priced. In an up market, exposure to diffusion beta and to jump beta is rewarded with larger returns. These exposures are penalized with greater losses during down markets. Consistent with CAPM, we present evidence that stocks with high sensitivities to jump systematic risk ask for higher returns, supporting a positive risk-return relationship. We also provide evidence that under extreme market movements, such as during the recent financial crisis, the absolute value of the beta premiums can differ substantially in significance and magnitude.

Overall, the results reveal that on average the response of each individual stock differs significantly with respect to continuous and discontinuous market movements highlighting the importance of decomposing the CAPM beta into diffusion and jump betas.

Chapter 3

Quantile Relationships between Standard Beta, Diffusion Beta and Jump Beta across Japanese Banks

3.1 Introduction

In the one factor capital asset pricing model (CAPM), systematic risk, measured by beta, is determined by the asset's covariance with the market over the market variance (Sharpe 1963; Lintner 1965). The traditional way of estimating the asset's constant beta has been by linear regression, typically based on 5 years of monthly data. However, the advent of even more powerful computers and easy access to high frequency data has revived interest in alternative non-parametric approaches to more accurately estimate betas. Compared with traditional parametric methods, a non-parametric approach using high frequency data trivializes calculation and avoids many distortive assumptions necessary for parametric modelling. Studies have shown that the use of high frequency data results in statistically superior beta estimates relative to the traditional regression based procedures (Bollerslev and Zhang 2003). In addition, unlike the constant beta computation, the realized beta computational approach allows a continuous evaluation of the time varying betas and thus provides a simple and robust estimator for measurement of time varying systematic risk, see, Wang et al. (2013).

From a pricing perspective, the empirical failure of the unconditional Capital Asset Pricing Model (CAPM) has led to three possible approaches to relaxing the overly restrictive CAPM assumptions. The first is to use additional systematic factors, as in Merton (1973), allowing extra-market factors to capture additional systematic risks. The ad-hoc three-factor model of Fama and French (1993) and the four-factor model of Carhart (1997) are some of the widely accepted examples of such multifactor models. The second approach is to relax the static relationship between expected return and risk by allowing time variation in the systematic factors. In that sense, Jagannathan and Wang (1996), Lettau and Ludvigson (2001) and Petkova and Zhang (2005) find that betas of assets with different characteristics move differently over the business cycle and Campbell and Vuolteenaho (2004), Fama and French (1996) and Ferson and Harvey (1999) show that time-variation in betas helps to explain anomalies such as value, industry and size. However, this conditional time-varying framework does not seem to be enough to improve the weak fit of the CAPM, as shown by Lewellen and Nagel (2006).

The third approach is the use of dual or conditional betas whereby the market beta is conditioned on market states, that is bullish or bearish or positive or negative market returns. Bhardwaj and Brooks (1993), Howton and Peterson (1998) and Pettengill et al. (1995) and among others have investigated the relationship between beta risk and stock market conditions. For example, Pettengill et al. (1995) observe that larger firms experience larges betas in down market conditions than in up market conditions, the reverse being true for smaller firms; Fabozzi and Francis (1977) first tested the stability of betas over the "bull" and "bear" markets. Using an alternative return decomposition method, Campbell and Vuolteenaho (2004) decomposes CAPM betas into discount rate betas and cash flow betas. Following Campbell and Vuolteenaho (2004), Botshekan et al. (2012) construct a return decomposition distinguishing cash flow and discount rate betas in up and down markets. They find that for larger companies, the priced components of risks become more symmetric (both upside and downside market).

In all of the above three approaches, the various beta estimates assume a continuous data generation process, while in fact the empirical papers in high frequency literature support the occurrence and persistence of jumps in the observed data generation process. A large body of literature has evolved to show both theoretically and empirically that jumps explain many of the dynamic features of stylized facts documented in asset prices. Studies on the stochastic behaviour of the stock market generally agree that stock returns are generated by a mixed process with a diffusion component and a jump component. If so, the standard CAPM beta is at best a 'summary proxy' for the systematic risk of a mixed-process, i.e. a weighted average of the diffusion component and the jump component. It would be prudent to be able to split the standard beta into two component betas so as to capture the two risks separately: one for continuous and small changes (diffusion beta) and the other for discrete and large changes (jump beta) as in Chapter 2. In this light, Todorov and Bollerslev (2010) provide a new theoretical framework for disentangling and estimating the sensitivity towards systematic diffusive and jump risk in the context of factor models. They focus on the decomposition of systematic risk by recognizing the jump occurrence at aggregate market level and show that diffusion and jump betas with respect to aggregate market portfolio differ significantly and substantially. Furthermore, the use of high frequency data ensures that both betas are also time-varying.

The key insight in this paper is that, though the continuous returns and jump returns are orthogonal by the Todorov and Bollerslev (2010) decomposition, the three realised betas (i.e. standard, diffusion and jump betas) are neither restricted nor expected to be orthogonal. In fact, a simple correlation test indicates some dependencies. The rich cross-sectional and time–series heterogeneity in our estimates of monthly betas enable us to study how standard beta, diffusion beta and jump betas vary both across quantiles and over time. To explore the cross-sectional relationships of the betas over quantiles, we adopt a quantile regressions (QR) approach. By doing so, it is possible to model the relationship between standard betas and diffusion and jump betas not just for the mean of the conditional distribution, but also at various quantiles. While the classical linear regression only describes the conditional mean, the quantile regression method allows us to estimate the effects of diffusion beta and jump beta on standard beta (e.g. Koenker and Hallock (2001)).

Our empirical investigations are based on high-frequency stock data of the 50 Japanese banks included in the Nikkei 225 index over the 2002-2012 sample period. We begin by estimating two separate betas; the diffusion and jump betas as well as a standard CAPM beta for each of the individual stocks on a monthly basis over the whole sample period. We rely on 5-minute intraday sampling frequency for the beta estimation, as a way to guard against the market microstructure complications that arise at the highest intraday sampling frequency. We regress the standard beta against the diffusion and jump beta and we find that the quantile regression relations between standard beta and diffusion and jump beta varies widely depending on the quantile level of standard beta, where the quantile ranges from zero to one.

We find that on average the standard beta is weighted more by the diffusion beta component then the jump beta component. The relationship holds across the quintiles. However, the actual magnitude of the weights differ across the quintiles. In general, the weights are jointly lower for low standard betas until the pick around the 50th-75th quintiles with value dropping down again post 75th quantile.

Sorting stocks based on the size, we find that large banks have high betas and small banks have low betas. The results holds for all the three betas; indicating that larger Japanese banks are more sensitive to market movements than smaller institutions, regardless of whether they occur through a jump or not. However, the ratios across the betas differ substantially. The ratios of large equity to small equity standard beta is 2.81 than the ratios of large equity diffusion beta over small equity diffusion beta is 5.81. On the other hand, the ratios of large equity to small equity jump beta is 1.16. Over and above this, a unique feature of small equity portfolio, is the jump-diffusion beta ratio, where the jump beta disproportionately is larger than its associated diffusion beta, indicating another layer of a possible size effect.

This study also makes a comparison between the jump-diffusion model and the conventional CAPM. At the 50th quantile, the hypothesis that standard beta is the weighted average of jump beta and diffusion beta cannot be rejected at 10% significance level. All other quantiles have rejection at 1% significance level. Empirical findings from this study agree with the model is that the systematic risk of an asset is the weighted average of both diffusion and jump risk.

The rest of the paper is organised as follows. In Section 3.2, we present our theoretical framework. Section 3.3 presents the methodology used in this study. Section 3.4 describes the data. The empirical analysis are present in Section 3.5. Section 3.6 describes the jump-diffusion model and the CAPM. Section 3.7 concludes the paper.

3.2 Theoretical framework

3.2.1 Capital asset pricing model

The standard capital asset pricing model (CAPM) is formulated as follows:

$$r_{i,t} = \alpha_i + \beta_{it} r_{m,t} + \varepsilon_{i,t} \tag{3.1}$$

where $r_{i,t}$ is the monthly excess stock return on stock *i*, and $r_{m,t}$ is the aggregate excess market returns at time *t*; α_i is the constant term for the asset *i ;* the error term $\varepsilon_{i,t}$ is the idiosyncratic risk of stock *i*, which is uncorrelated with r_m or the idiosyncratic risk of any other stock under CAPM assumptions. The slope coefficient, $\beta_{i,t}$, in Equation (3.1), commonly known as the Standard Beta, is the systematic risk of asset *i*, and measures the responsiveness of the changes in stock's prices to changes in market prices. According to the CAPM, the equilibrium expected return on all risky assets are a function of the covaraiance with the market portfolio.

The Standard Beta, in CAPM is defined as,

$$\beta_{i,t} = \frac{Cov(r_{i,t} r_{m},t)}{Var(r_{m},t)} \tag{3.2}$$

The CAPM model basically depends on stock and market returns, which in turn, depends the underlying prices of individual stocks. It is now widely agreed in the literature that financial return volatilities and correlations are time-varying and returns follow the sum of a diffusion process and a jump process.[26]

We consider that the log-price (p_t) process of an asset at time t follows a continuous-time jump-diffusion process defined by the stochastic differential equation as follows:

$$dp_t = \mu_t dt + \sigma_t dW_t + k_t dq_t \tag{3.3}$$

where μ_t is the instantaneous drift of price process and σ_t is the diffusion process; W_t is standard Brownian motion. These first two terms correspond to the diffusion part of the total variation process. The diffusion part is responsible for the usual day-to-day price movement. These changes in stock prices may be due to variation in capitalization rates, a temporary imbalance between supply and demand, or the receipt of information which only marginally affects stock prices. The final term, $k_t dq_t$ refers to the jump component of the total process, where q_t is a counting process such that $dq_t = 1$ indicates a jump at time t and $dq_t = 0$ otherwise and k_t is the size of jump at time t if a jump occurred. The jump part is due to the receipt of any important information that causes a more than marginal change (i.e. abnormal change) in the price of stock. The arrival of this kind on information is random and the number of such information arrivals is assumed to be distributed according to a Poisson process. If the return of stocks should be divided into jump part and diffusion part the risk associated with returns of securities should be decomposed into two parts also, as seen in Chapter 3.

3.2.2 Decomposing systematic risk: diffusion and jump components

Our framework motivating the different betas and the separate pricing of diffusion and jump market price risk relies on the theory originally developed by Todorov and Bollerslev (2010) for decomposing market returns into two components: one associated with diffusion price

[26] See, for example, Press (1967), Merton (1976), and Ball and Torous (1983) and among others.

movement and another associated with jumps. Hence in the presence of both components, equation (3.1) becomes:

$$r_{i,t} = \alpha_i + \beta^c_{i,t} r^c_{m,t} + \beta^j_{i,t} r^j_{m,t} + \varepsilon_{i,t} \tag{3.4}$$

where the total market return ($r_{m,t}$) is decomposed into the diffusion return ($r^c_{m,t}$) and the discontinues (jump) market return $\left(r^j_{m,t}\right)$. Correspondingly, the systematic risk also comprises two components, diffusion beta (β^c_{it}), and jump beta (β^j_{it}), which represents the sensitivities of *i*th asset return to $r^c_{m,t}$ and $r^j_{m,t}$. If the systematic risks exposure of a firm to both diffusion and jump price movements are identical, i.e. $\beta^c_{i,t}$ = $\beta^j_{i,t}$, equation (3.4) would be equivalent to equation (3.2). However, if, $\beta^c_{i,t} \neq \beta^j_{i,t}$, the beta computed from equation (3.2) may be used to identify the reactiveness of an asset return of the two components of systematic risk, denoted by $\beta^c_{i,t}$ and $\beta^j_{i,t}$ respectively.

We have shown that market returns contain two components, both of which display substantial volatility and which are not highly correlated -with each other. This raises the possibility that different types of stocks may have different betas with two components of the market. Chen (1996) shows that under the same assumption of CAPM, except the normality of asset returns, the jump-diffusion model takes two different types of beta when pricing the underlying asset. One is diffusion beta, which measures the systematic risk when no jumps occurs. The other is the jump beta, which measures the systematic risk when jumps take place in the market. In a similar form to that of CAPM, the jump-diffusion two beta model is as follows:

$$r_{i,t} = \alpha_i + r_{m,t}[(1-\emptyset)\beta^c_{i,t} + \emptyset\beta^j_{i,t}] + \varepsilon_{i,t} \tag{3.5}$$

The left hand side of (4.5) is the monthly stock return on asset *i*. The right hand side of (4.5) is weighted average of two betas: the diffusion beta, with a weight of $(1-\emptyset)$ and the jump beta, with a weight of $\emptyset$. β^c_{it} is the diffusion beta as defined by $\beta^c_{i,t} = \frac{Cov(r_{i,t} r^c_{m,t})}{Var(r^c_{m,t})}$;

β^j_{it} is the jump beta as defined by $\beta^j_{i,t} = \frac{Cov\left(r_{i,t} r^j_{m,t}\right)}{Var\left(r^j_{m,t}\right)}$. If there are no jumps in the market, $k = 0$ which implies $\emptyset = 0$, and equation (3.5) collapses to the conventional CAPM,

$$r_{i,t} = \alpha_i + r_{m,t}[\beta^c_{i,t}] + \varepsilon_{i,t} \tag{3.5a}$$

On the other hand, if asset returns are generated by a pure jump process, $\sigma^2(r_m) = 0$ which implies$\emptyset = 1$, then equation (3.5) reduces to pure jump CAPM,

$$r_{i,t} = \alpha_i + r_{m,t}[\beta_{i,t}^{j}] + \varepsilon_{i,t} \tag{3.5b}$$

Equation $(3.5a)$ and $(3.5b)$ are two special cases of equation (3.5), the jump-diffusion two-beta asset pricing model.[27] The two-way decomposition beta allows us to ask how individual equity prices respond to diffusion and jump market moves.

3.3 Methodology

In this paper we study the relationship between standard beta, diffusion beta and jump beta across Japanese banks, building on the analysis of the previous chapter.

3.3.1 Realized beta

Standard betas are not directly observable. The traditional way of addressing the estimation problem of betas has relied on using rolling linear regressions, typically requiring 5 years of monthly data to satisfy sample size requirements.[28] However, the advent of readily available high frequency data in recent years, have now made it possible to compute realized betas over varying frequencies that can be used as proxies for standard betas.

Realized beta is defined as the ratio of realized covariance of stock and market to the realized market variance. Andersen et al. (2005) argue that realized beta is a more accurate measurement of the standard beta because it employs more information than the traditional regression on monthly returns.

The estimate of realized beta for individual stock, $\hat{\beta}_{i,t}^{s}$ is defined as:

$$\hat{\beta}_{i,t}^{s} = \frac{RCOV_{i,t,s}^{s}}{RV_{m,t,s}^{s}} = \frac{\sum_{s=1}^{n} r_{i,t,s}\, r_{m,t,s}}{\sum_{l=1}^{n} \left(r_{m,t,s}\right)^2} \tag{3.6}$$

Despite the numerous advantages of realized beta, it is important to note that equation (3.6) still defines the standard beta in a one-factor CAPM model.

The same readily high frequency data that made possible the computation of the realized betas has also made possible the disentanglement of these realized betas into diffusion betas and

[27] See, Chen (1996) for more details.
[28] see, e.g., the classical work by Fama and MacBeth (1973).

jump betas, thus effectively giving rise to a two-factor CAPM model for pricing assets which follow not only a diffusion process but also a jump process.

3.3.2 Diffusion and jump betas

We follow the procedure proposed by Todorov and Bollerslev (2010) to estimate the diffusion beta and jump beta for each individual stock. See section 2.2.2 in Chapter 2 from more details.

3.4 Sample and data

The sample and data section draw on the same data set described in Chapter 2, Section 2.3.

3.5 Empirical results

3.5.1 Betas

Our main empirical results are based on monthly standard, diffusion and jump beta estimates for each of the stocks in the sample. We rely on fixed intraday sampling frequency of 5 minutes in our estimation of the standard, diffusion and jump betas, with the returns spanning 9.05am to 3.00pm. We compute the means and standard deviations of the time varying betas for period 2003- 2012 and three sub periods (pre-crisis period, crisis period and post-crisis period) and present the results in Table 3.1. The statistics show that the jump beta has a higher mean of 0.912 and volatility of 0.626, relative to the 0.501 and 0.280; and 0.324 and 0.309 estimated for standard betas and diffusion betas respectively for the sample period. The difference in means of diffusion beta and jump beta (0.65) are significant based on the pooled variance t-tests. When we split the period into three sub periods: pre-crisis, crisis and post-crisis period, we see a clear contrast in the means and standard deviation between three betas. The standard, diffusion and jump betas are higher and more volatile in crisis period compared to pre-crisis and post-crisis period.

Table 3.1: Summary statistics for standard, diffusion and jump betas.

	Standard Beta	Diffusion Beta	Jump Beta
Full-sample Period			
Mean	0.501	0.280	0.912
Std.Dev	0.324	0.309	0.626
t-test of difference		-0.649***	
Pre-crisis Period			
Mean	0.390	0.223	0.759
Std.Dev	0.276	0.276	0.572
t-test of difference		-0.557***	
Crisis Period			
Mean	0.702	0.452	1.095
Std.Dev	0.342	0.321	0.746
t-test of difference		-0.647***	
Post-crisis Period			
Mean	0.548	0.248	1.042
Std.Dev	0.306	0.308	0.552
t-test of difference		-0.819***	

Note: The table summarizes the time varying betas estimated using the Jump-Diffusion CAPM model. The statistics include mean and standard deviations (in parentheses) for the full sample periods and three sub-periods. We include the pooled variance t-test of the difference between the two sample means for the standard beta, diffusion beta and jump beta. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

To get a sense of what the relationship across the different betas looks like, Figure 3.1 plots the kernel density estimates of the unconditional distributions of the three different betas averaged across time and stocks. The jump betas tend to be somewhat higher on average and also more right skewed than the diffusion and standard betas. At the same time, the figure also suggests that the diffusion betas are the least dispersed of the three betas across time and stocks. Part of the dispersion in the betas could be attributed to estimation errors.[29]

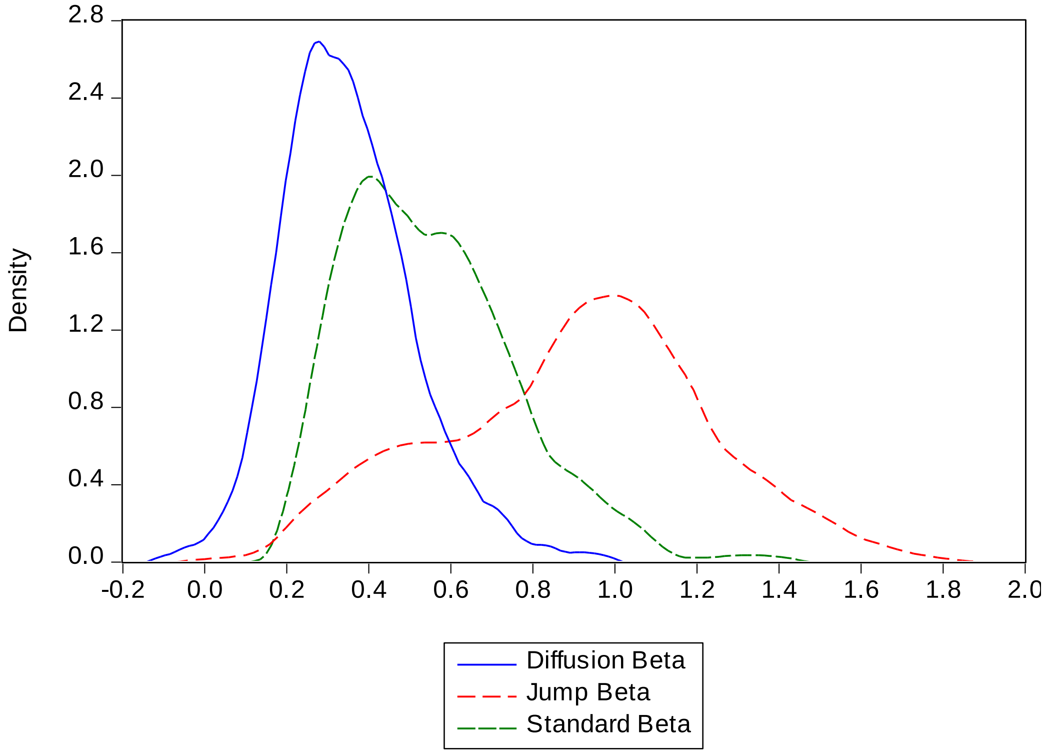
In order to visualize the temporal and cross-sectional variation in different betas, Figure 3.2 shows that the time series of equally weighted portfolio betas, based on monthly quintile sorts for each of the three different betas and all of the individual stocks in the sample. The figure suggests that the variation in the standard beta and diffusion beta sorted portfolios in Panel A and B are clearly fairly close, as would be expected. The plots for the jump beta quintle portfolios in Panel C, are distinctly different and more dispersed than the standard and diffusion

[29] Based on the expressions derived in Todorov and Bollerslev (2010), Bollerslev et al. (2015) report that the asymptotic standard errors for diffusion and jump betas averaged across all of the stocks and months in the sample equal 0.06 and 0.12, respectively, compared with 0.14 for the conventional OLS- based standard errors for the standard beta estimates.

betas quintile portfolios. Jump beta is significantly different from diffusion and standard beta. Motivated by these above findings and in order to shed light on this issue in the face of the significant heterogeneity observed across the Japanese banking sector, we depart from the previous literature and employ quantile regression analysis to estimate the relationship between standard, diffusion and jump betas.

Overall, our estimates shows that there is interesting variation across assets and across time in the two components of the market beta. Consistent with Chapter 3, we confirm that stocks have higher jump betas than diffusion betas.

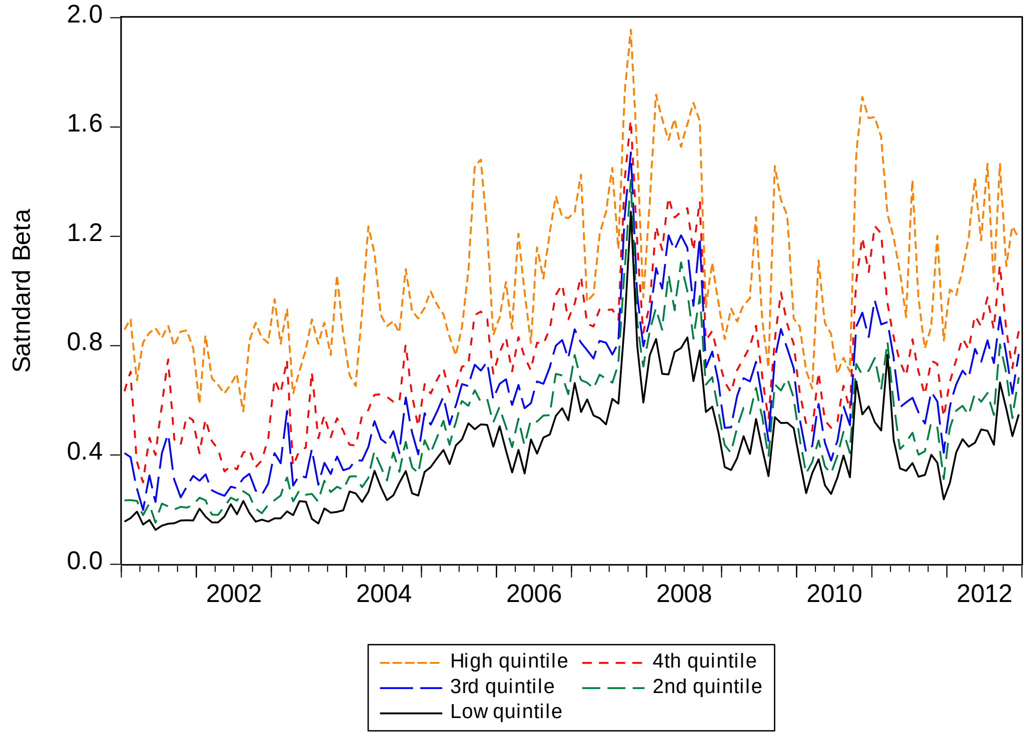
Figure 3:1: Distributions of betas



Note: The figure displays kernel density estimates of the unconditional distributions of the three different betas averaged across firms and time.

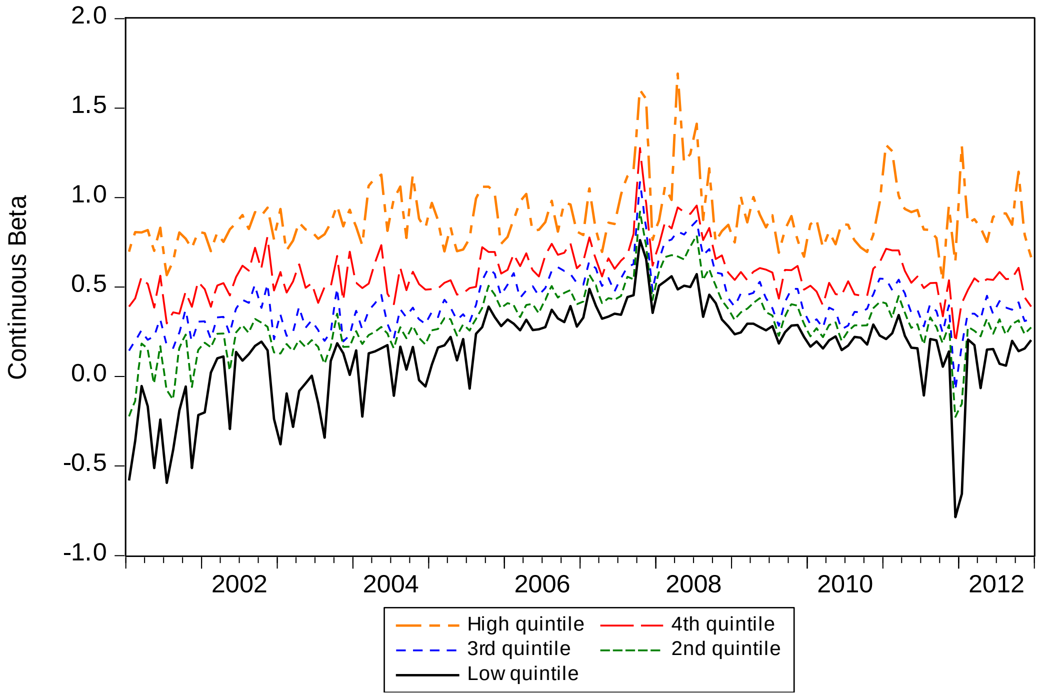
Figure 3:2: Time series plots of betas

Panel (A): Standard beta

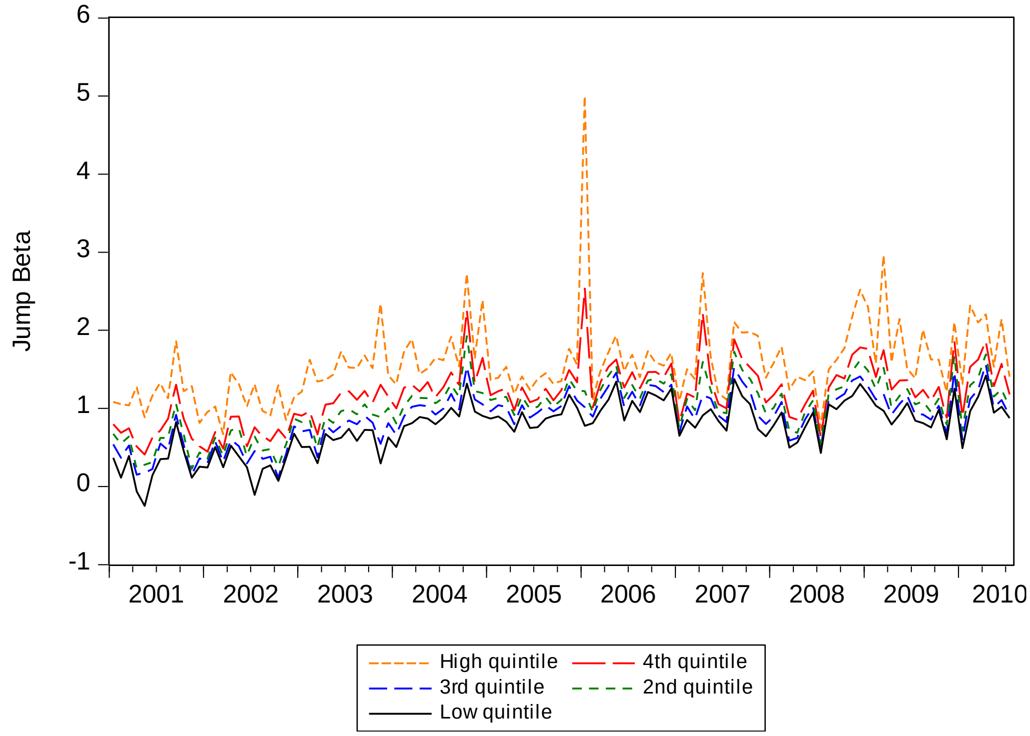


Note: The figure displays the time series of betas for equally weighted beta-sorted quintiles portfolios. Panel A shows the result for the standard beta sorted portfolios, Panel B the diffusion beta sorted portfolios and Panel C the jump beta sorted portfolios.

Panel (B): Diffusion beta



Panel (C): Jump beta



3.5.2 Quantile regression model

An ordinary least squares determines the average relation between the dependent and a set of relevant explanatory variable. It focuses on the estimation of the conditional mean, whereas a quantile regression (QR) model allows us to estimate the relationship between a dependent and independent variables at specific quantiles. Moreover, it is well know that quantile regression is robust to heteroskedasticity, skewness and leptokurtosis, which are the features of financial data (Koenker and Xiao 2006). Thus, quantile regression methodology provides a better picture in testing how the relationship between diffusion and jump betas vary across quantiles of the conditional distribution.

The quantile regression approach has been widely used in many areas of applied economics and econometrics such as the investigation of wage structure (Buchinsky 1994) earnings mobility (Trede 1998; Eide and Showalter 1999), and educational quality issues (Eide and Showalter 1998; Levin 2001). There is also growing interest in employing quantile regression methods in the financial literature. Applications in this field include work on Value at Risk (Taylor 1999; Chernozhukov and Umantsev 2001; Engle and Manganelli 2004), option pricing (Morillo 2000), and the analysis of the cross section of stock market returns (Barnes and

Hughes, 2002), return distributions (Allen et al. 2013), mutual fund investment styles (Bassett Jr and Chen 2002), the investigation of hedge fund strategies (Meligkotsidou et al. 2009), the return- volume relation in the stock market (Chuang et al. 2009), and the diversification and firm performance relation (Lee and Li 2012). Following this line of thought, a QR technique developed by Koenker and Bassett Jr (1978) is used in this study to examine the relationship between the standard beta, diffusion beta and jump beta.

The quantile regression takes the following form

$$y_i = x'_i b^\tau + \varepsilon_i^\tau \tag{3.7}$$

where y_i is the dependent variable of interest and x_i the vector of predictor variables. The parameter vector b^τ is associated with the τ-quantile while ε_i^τ is the error term, allowed to have a different distribution across quantiles. Note that the local effect of x_i on the τ-quantile is assumed to be linear. The slope coefficient vector b^τ differs across quantiles and the estimator for $b^\tau$is obtained from

$$\begin{aligned} min \sum_{i:\varepsilon_i^\tau > 0} \tau \times |\varepsilon_i^\tau| + \sum_{i:\varepsilon_i^\tau < 0} (1-\tau) \times |\varepsilon_i^\tau| \\ = \sum_{i:y_i - x'_i\beta^\tau \geq 0} \tau \times |y_i - x'_i b^\tau| + \sum_{i:y_i - x'_i\beta^\tau < 0} (1-\tau) \times |y_i - x'_i b^\tau| \end{aligned} \tag{3.8}$$

The quantile function is estimated by minimizing a weighted sum of absolute residuals, where the weights are functions of the quantiles of interest. The coefficient estimates are computed using linear programing methods. For more details, see, Koenker (2005). For $\tau = 0.5$, i.e., the conditional median of x, the problem collapses to the well known least absolute deviation (LAD) estimation. The value of b can be obtained using linear programming algorithms and standard errors can be bootstrapped. We conduct the minimization procedure at quantiles of $\tau = 0.05, 0.25, 0.50, 0.75, 0.95$ and thus obtain a full picture of the relationship between dependent and independent variables across the whole distribution of the former, not just for its mean value.

3.5.3 Quantile regression analysis

As a preliminary exercise, we first explore what OLS regressions say about the relationships of the three beta across Japanese banks. Table 3.2 presents the results from OLS regressions to explain the cross-sectional and time series variation in the standard betas as a function of the variation in the two other betas, diffusion and jump betas. Model (1) in Table 3.2 shows that the diffusion beta exhibits the highest explanatory power for standard beta, with an average adjusted R-squared of 0.64. To get an impression of the contribution of jump betas, we include model (2). The jump beta explain 48% variation in standard beta. When we add the diffusion beta and jump beta as in model (3), we see that altogether, 80 % of the variation in standard beta may be accounted for by the high frequency betas, with diffusion beta having by far largest and most significant effect. It is also noted that the OLS regression results is consistent with our earlier results in Figures 3.1 and 3.2.

Table 3.2: The relationship between standard, diffusion and jump betas across Japanese banks

Dependent Variable=Standard Beta			
	(1)	**(2)**	**(3)**
Diffusion Beta	0.874***		0.678***
	(0.029)		(0.027)
Jump Beta		0.362***	0.229***
		(0.022)	(0.011)
Constant	0.257***	0.164***	0.107***
	(0.013)	(0.015)	(0.008)
R-squared	0.64	0.48	0.80

Note: **Standard errors** are displayed in parentheses below the **coefficients**. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

However, it should be noted that the OLS estimator focuses only on the central tendency of distributions. Therefore, they do not allow us to examine the relationship between the three betas in non-central regions. A quantile regression offers more information as it looks at whether coefficients change significantly across quantiles. To help further gauge this relations, the QR analysis used in this paper to investigate how the standard, diffusion and jump betas are related to each other at their various quantiles.[30]

The quantile regression procedures yields a series of quantile coefficients, one for each sample quantile. We may thus test whether standard beta respond differently to changes in the regression depending on whether the bank is in the left tail of distribution (low risk bank) or in

[30] We proceed to examine the relations relationship between standard beta, diffusion beta and jump beta across Japanese bank using the following quantile regression model:

$$Q(\tau)_{\beta^s}\ (\beta^s_{i,t}) = a_0(\tau) + b_1(\tau)\beta^c_{i,t} + b_2(\tau)\beta^j_{i,t} + \varepsilon_{i,t}$$

The variable of primary interest is the coefficient of diffusion and jump betas on the standard betas. The slopes of the regressors are estimated at five different quantiles τ −the 5th, 25th, 50th, 75th, 95th- using the same set of explanatory variables for each quantile.

the right tail of the distribution (high risk bank). In Table 3.3, we present the parameter estimates for selected quantiles ranging from 0.05 to 0.95. A closer look at the individual conditional quantiles reveals that the relation between standard, diffusion and jump betas changes in magnitude across the distribution quantiles. For example, while the response rate for diffusion beta and jump beta at the 5th quantile are, respectively, 0.55 and 0.16, at the median they are 0.71 and 0.28, and at the 95th quantile they are 0.68 and 0.22. All coefficients are strongly statistically different from zero. Additionally, our results show that the conditional mean approach is also misleading in terms of goodness-of-fit. While the R-squared of 0.80 of the conditional mean would suggest that the convariates are relatively successful at explaining the variation in standard beta, the quantile regressions show that while this is true for high-risk firms (for example, the pseudo R-squared at the 75th quantile is 0.60), for low-risks firms the empirical variables have much less explanatory power (for example, the pseudo R-squared at the 5th quantile is 0.48). This indicates that high risk firms are more sensitive to diffusion risks than the jump risks compared with low risk firms.

In order to check the significance of the differences with regard to the coefficients of diffusion beta and jump beta across different quantiles, this study employs a bootstrap procedure extended to construct a joint distribution to test various pairs of quantiles (Chuang et al. 2009). Table 3.4 presents the F-test results for the null hypothesis of equal slopes across quantiles to formally test whether the slopes of explanatory variables change across quantiles. These results indicate that the coefficients are significantly different from each other between all quantiles. Further, we observe that there are significant differences between the coefficient of 5th quantile and 95th quantile, supporting the notion that at low and high of standard betas within the Japanese banking sector the relationships between standard, diffusion and jumps betas differ significantly. More importantly our results indicate that the relationship may be far more complicated than can be described using least-squares regression. Indeed, the relationships between standard betas, diffusion betas and jump betas for Japanese banking stock may be non-linear across quantiles and the relationships at tail quantiles may be quite different from those at middle quantiles and at the mean.

Table 3.3: The relationship between standard beta, diffusion beta and jump beta different quantiles

Dependent Variable= Standard Beta					
	5th quant	**25th quant**	**50th quant**	**75th quant**	**95th quant**
Diffusion Beta	0.555***	0.689***	0.709***	0.684***	0.677***
	(0.025)	(0.012)	(0.010)	(0.012)	(0.028)
Jump Beta	0.157***	0.245***	0.281***	0.291***	0.222***
	(0.006)	(0.004)	(0.006)	(0.010)	(0.018)
Constant	-7.77e-16	-3.28e-15	0.0410***	0.120***	0.376***
	(0.003)	(0.000)	(0.005)	(0.008)	(0.018)
Pseudo R-squared	0.48	0.58	0.61	0.60	0.53

Note: **Standard errors** are displayed in parentheses below the **coefficients**. Standard errors are obtained by bootstrapping with 100 replications. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Table 3.4: Post estimation linear hypothesis testing

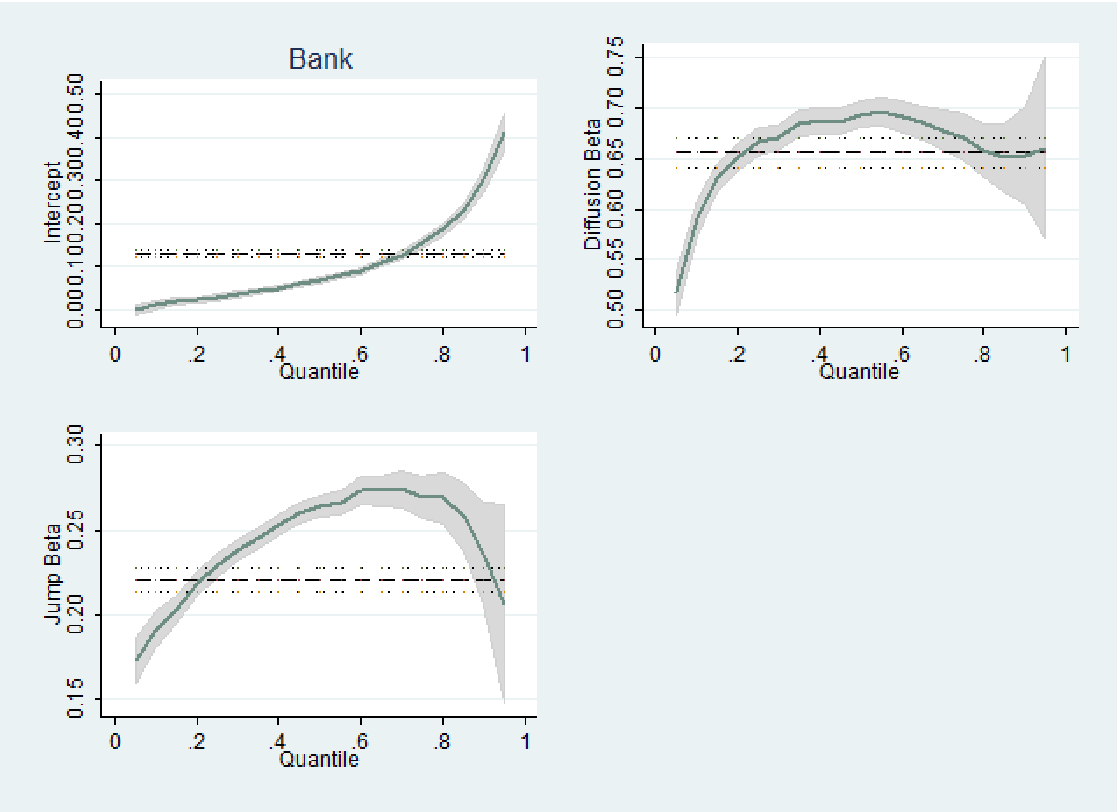
H0: Test whether diffusion beta and Jump beta coefficients are equal across different quantiles	
H0: Q5=Q25	F(2, 5401) =214.87***
	Prob > F = 0.0000
H0: Q25=Q50	F(2, 5401) = 48.98***
	Prob > F = 0.0000
H0: Q50=Q75	F(2, 5401) = 3.18**
	Prob > F = 0.0417
H0: Q75=Q95	F(2, 5401) = 10.92***
	Prob > F = 0.0000
H0: Q05=Q95	F(2, 5401) = 22.42***
	Prob > F = 0.0000
H0: Q25=Q75	F(2, 5401) = 23.40***
	Prob > F = 0.0000

Note: The table presents F-test for testing whether coefficients between different quantile are equal. Quantiles have been estimated by simultaneous regression analysis. Standard errors were obtained by bootstrapping with 100 replications. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Figure 3.3 graphically shows how the beta values vary across quantiles. The figure depicts point estimates of the slope of explanatory variable along with a 95% pointwise confidence band. The vertical axis measures the magnitude of the coefficient, and the horizontal axis measures the quantiles. The horizontal axis lists quantiles running from 0.05 through 0.95.

If the assumptions for the standard linear regression model hold, the quantile slope estimates should fluctuate randomly around a constant level, with only the intercept parameters systematically increasing with τ. However, none of the slope estimates of the variables could be described as random fluctuations here. In fact, the quantile slope estimates of the variables such as diffusion beta jump beta follow a systematic pattern with low values in the left tail and high values in the right tail. These two variables are significant in the tail parts of the distribution, but have little impact in the middle. It is apparent that the slope of regression changes across the quantiles and is clearly not constant, as presumed in OLS. The results indicate that on average the jump betas for a quantile are higher than the corresponding diffusion betas. However, companies with low quantile standard betas are less sensitive to market jumps as compared to companies with high quantile standard betas.

Figure 3:3: Quantile plot of estimated slopes and 95% confidence interval

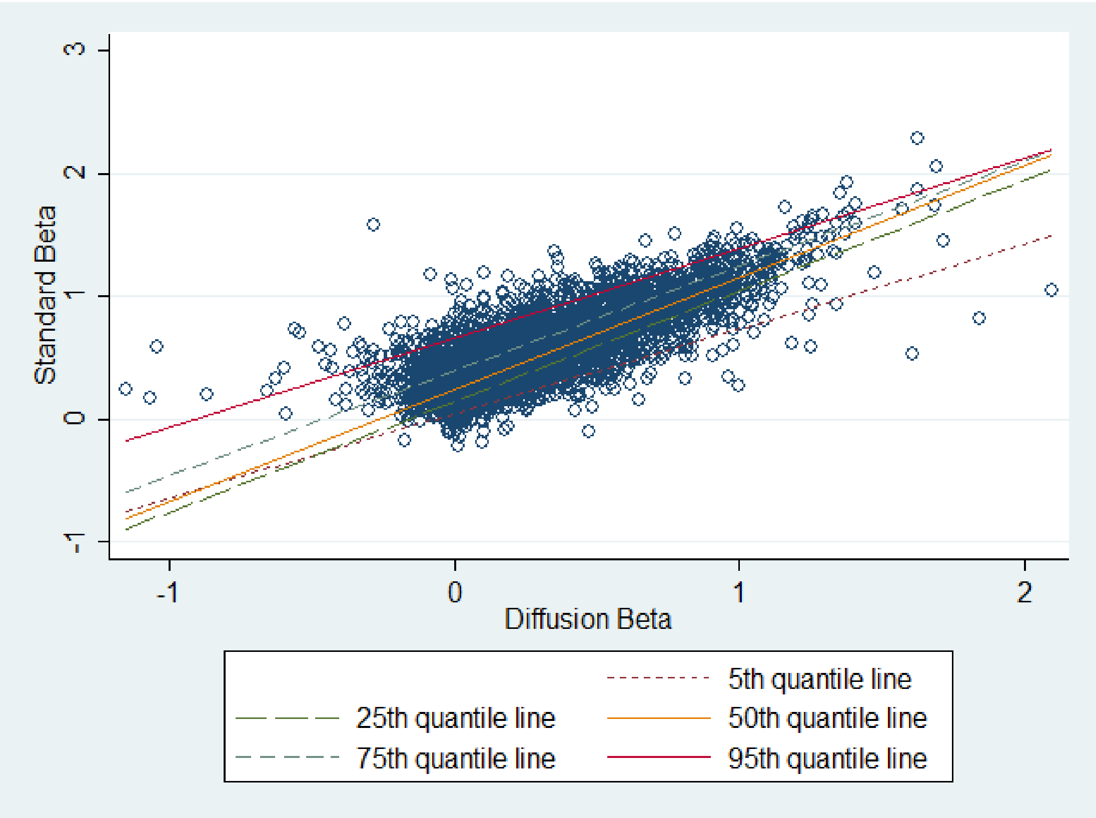


Note: The solid line gives the coefficients of diffusion beta estimates from the quintile regression, with the shaded grey area depicting a 95% confidence interval. The dashed line gives the OLS estimate of mean effect, with two dotted lines again representing a 95% confidence interval for this coefficient.

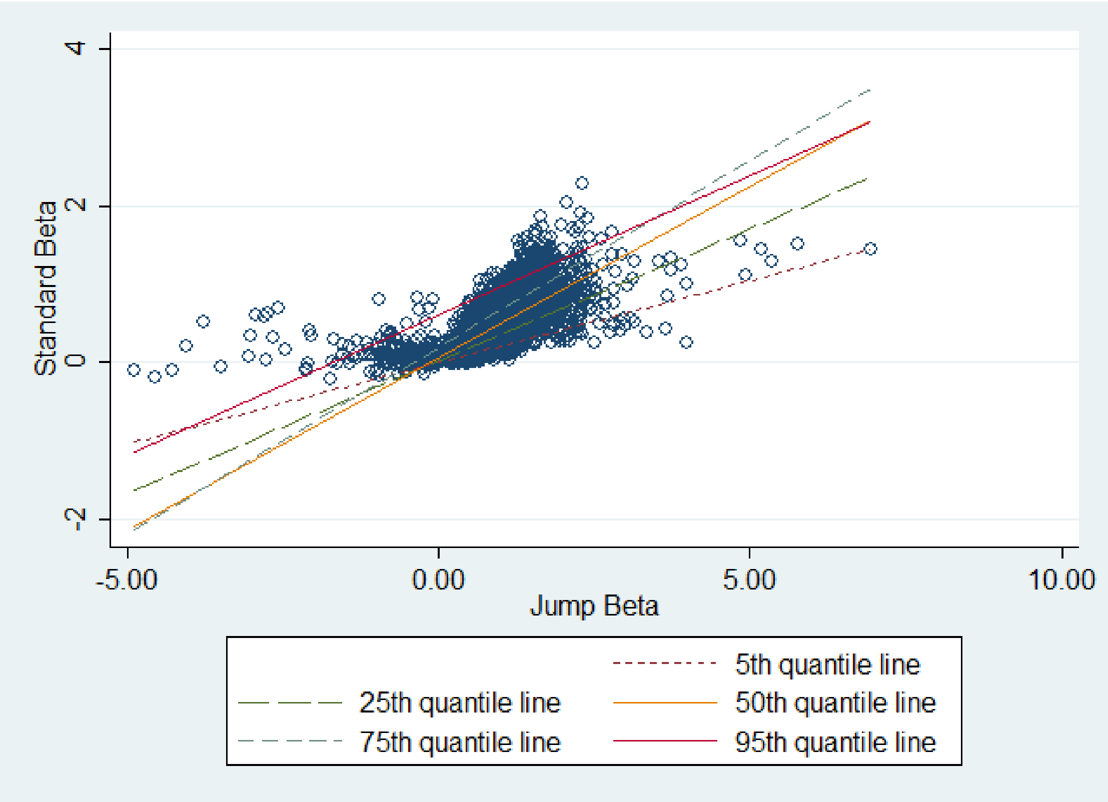
Figure 3.4 shows the scatter plots of the monthly standard betas versus diffusion betas and monthly standard beta versus jump betas for quantile regressions for quantiles= 0.05, 0.25, 0.50, 0.75 and 0.95 respectively. The scatter plot in panel A of Figure 3.4 suggests heteroskedasticity in the dataset, given that the dispersion of results seems to somewhat smaller in the middle of the distribution. The estimated fit lines for the 5th, 50th, 95th quantiles shown in the panel A, indicate that for firms which are relatively risky in terms of standard beta- in other words, firms to the right of the distribution – the diffusion beta to the 5th and 95th quantiles are not very different. But unlike the case of panel B, the gap between the 5th and 95th quantiles is higher on the right side of the graph; in other words, amongst those firms the jump beta to the 5th and 95th quantiles are quite different. It indicates that when the distribution reaches extremes, the diffusion betas and jump betas behave differently from those in or around median observation.

The general conclusion that can be drawn is that there exists a wide disparity in behaviour between high risk firms and low risk firms that may be receiving diffusion and jump shocks, and that such behaviour differs for high risk firms as opposed to low risk firms. The quantile regression technique provides considerable insight that cannot be obtained by using standard regression techniques. The differences in information content of the betas also manifest in different relations with underlying diffusion and discontinuous price variation.

Figure 3:4: Scatterplot of Betas across different quantiles
Panel A: Standard beta and diffusion beta



Panel B: Standard beta and jump beta



3.5.4 Size-sorted portfolios

It is often implicitly assumed that small and large banks behave differently. To control further for possible size effects, we test the relationship between standard beta, diffusion beta and jump beta using 5 subsamples constructed by sorting the data with respect to size. Tables 3.5 and 3.6 report results for portfolios sorted on stock size, where the portfolios are rebalanced each year. Banks are grouped into five benchmark portfolios ranked by size, based on market capitalization at the end of each year *t*. Portfolio 1 includes the smallest banks in the group and portfolio 5 includes largest banks in the sample. Table 3.4 shows a clear effect of size on the estimated coefficient for the jump-diffusion model. The diffusion beta coefficient is lower for the largest quintiles and the decline is statistically significant. For the jump beta, the decrease for large-cap companies is much less strong, although also statistically significant. We apply a quantile regression methodology in Table 3.6 to estimate the relationship between different betas and we obtain the same results as those from Table 3.5.

Comparing the relative magnitude of the different coefficients, we see that for small companies jump components are the dominant ingredients. For large companies, however, it is predominantly the diffusion component. The results lead us to conclude that the jump risk is much more relevant for small companies than diffusion risk. If well-established companies are considered, a much more symmetric notion of stock market risk appears to apply, mainly relating to diffusion risk rather than to jump risk.

Table 3.5: The relationship between standard beta, diffusion beta and jump beta across for size-sorted stock portfolios

Dependent Variable= Standard Beta					
	Small	**2**	**3**	**4**	**Big**
Diffusion Beta	0.600***	0.685***	0.740***	0.469***	0.573***
	(0.043)	(0.066)	(0.047)	(0.063)	(0.026)
Jump Beta	0.192***	0.199***	0.215***	0.271***	0.203***
	(0.015)	(0.018)	(0.021)	(0.020)	(0.016)
Constant	0.103***	0.112***	0.107***	0.161***	0.242***
	(0.013)	(0.012)	(0.013)	(0.026)	(0.019)
R-squared	0.67	0.71	0.79	0.70	0.73

Note: **Standard errors** are displayed in parentheses below the **coefficients**. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Table 3.6: The relationship between standard beta, diffusion beta and jump beta across different quantiles for size-sorted stock portfolios

Dependent Variable= Standard Beta					
	5th quant	**25th quant**	**50th quant**	**75th quant**	**95th quant**
	Small				
Diffusion Beta	0.329***	0.510***	0.632***	0.638***	0.665***
	(0.049)	(0.042)	(0.049)	(0.032)	(0.052)
Jump Beta	0.170***	0.195***	0.224***	0.225***	0.185***
	(0.012)	(0.010)	(0.013)	(0.019)	(0.036)
Constant	-0.019**	0.029***	0.064***	0.133***	0.308***
	(0.009)	(0.006)	(0.009)	(0.015)	(0.036)
Pesudo R-squared	0.39	0.40	0.42	0.44	0.45
	2				
Diffusion Beta	0.498***	0.624***	0.638***	0.717***	0.656***
	(0.048)	(0.053)	(0.042)	(0.035)	(0.044)
Jump Beta	0.142***	0.205***	0.248***	0.259***	0.192***
	(0.015)	(0.012)	(0.010)	(0.019)	(0.032)
Constant	0.006	0.030***	0.063***	0.122***	0.354***
	(0.005)	(0.005)	(0.006)	(0.014)	(0.029)
Pesudo R-squared	0.40	0.47	0.50	0.49	0.47
	3				
Diffusion Beta	0.558***	0.690***	0.762***	0.736***	0.760***
	(0.064)	(0.045)	(0.031)	(0.030)	(0.047)
Jump Beta	0.157***	0.223***	0.244***	0.262***	0.209***

	(0.017)	(0.017)	(0.012)	(0.020)	(0.026)
Constant	-0.006	0.022**	0.071***	0.141***	0.357***
	(0.008)	(0.011)	(0.008)	(0.015)	(0.021)
Pesudo R-squared	0.45	0.51	0.56	0.57	0.56
	4				
Diffusion Beta	0.265***	0.463***	0.540***	0.524***	0.512***
	(0.060)	(0.040)	(0.027)	(0.026)	(0.053)
Jump Beta	0.213***	0.276***	0.316***	0.339***	0.292***
	(0.025)	(0.016)	(0.016)	(0.026)	(0.034)
Constant	0.040***	0.058***	0.081***	0.163***	0.397***
	(0.014)	(0.011)	(0.013)	(0.024)	(0.041)
Pseudo R-squared	0.38	0.47	0.48	0.49	0.49
	Big				
Diffusion Beta	0.630***	0.591***	0.590***	0.570***	0.540***
	(0.043)	(0.033)	(0.022)	(0.031)	(0.048)
Jump Beta	0.170***	0.257***	0.260***	0.225***	0.170***
	(0.027)	(0.028)	(0.021)	(0.024)	(0.025)
Constant	-3.33e-16	0.081**	0.158***	0.296***	0.563***
	(0.002)	(0.033)	(0.021)	(0.028)	(0.038)
Pseudo R-squared	0.54	0.52	0.50	0.48	0.45

Note: Regression results between standard beta, diffusion beta and jump beta across different quantiles. **Standard errors** are displayed in parentheses below the **coefficients**. Standard errors are obtained by bootstrapping with 100 replications. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

3.5.5 Size effect on betas

The effect of size on bank systematic risk is debated. Demsetz and Strahan (1997) find that large banks are internally diversified and this provides one means of reducing bank systematic risk. However, Saunders et al. (1990) and Anderson and Fraser (2000) find that large banks with greater sensitivity to the general market movements than small banks leading to a positive relation between bank systematic risk and size. Therefore, it is important to recognize that there is an association between size and different betas. We test if the time varying betas are related to the size portfolios. Table 3.7 presents the mean and standard deviations of the standard, diffusion and jump betas for the small and large portfolios. We report the t-statistics for the test of the hypothesis that the difference between small and large is zero. We find that in all cases there is negative and statistically different between the betas of small and large banks indicating that large banks react more severely than small banks. The results support that larger Japanese banks are more sensitive to market movements than smaller institutions, regardless of whether they occur through a jump or not

Table 3.7: Characteristics of time varying betas

	Large equity portfolio			Small equity portfolio		
	Standard Beta	**Diffusion Beta**	**Jump Beta**	**Standard Beta**	**Diffusion Beta**	**Jump Beta**
Full-sample Period						
Mean	0.814	0.576	1.165	0.290	0.099	0.707
Std.Dev	0.282	0.319	0.630	0.203	0.173	0.595
t-test of difference	-0.524***	-0.478***	-0.457***			
Pre-crisis Period						
Mean	0.720	0.528	1.080	0.159	0.036	0.443
Std.Dev	0.252	0.300	0.508	0.109	0.101	0.513
t-test of difference	-0.561***	-0.492***	-0.637***			
Crisis Period						
Mean	0.988	0.752	1.251	0.438	0.226	0.868
Std.Dev	0.266	0.254	0.955	0.230	0.211	0.712
t-test of difference	-0.550***	-0.526***	-0.382***			
Post-crisis Period						
Mean	0.888	0.527	1.306	0.316	0.073	0.830
Std.Dev	0.267	0.363	0.449	0.181	0.152	0.516
t-test of difference	-0.572***	-0.454***	-0.476***			

Note: The time varying betas estimated using the Jump-Diffusion CAPM model. Statistics include mean and standard deviations (in parentheses) are summarized by the full sample periods and three sub-periods. We report time varying betas for two size-sorted equity portfolios (large size equity beta portfolio, and small size equity beta portfolio). We include the pooled variance t-test of the difference between the two sample means for the Standard Beta, Diffusion Beta and Jump Beta and also the size-sorted equity portfolio. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

A notable point is that although betas for large firms are larger than the small firms, for large equity portfolios, the jump-diffusion beta ratio is lower than the jump-diffusion beta ratio of the small equity portfolio. The means for small equities, the influence of jump beta is proportionately much larger compared with large equity portfolios. This is further corroborated by the larger magnitude of the constants for large portfolios than small portfolios (see Table 3.5 and 3.6). Small portfolios equities are more sensitive to large surprises than the large portfolio equities. The explanation for this phenomenon is that small bank equities are riskier than large bank equities because less information is available about the former than about the latter. Therefore, small bank portfolios react more severely to surprises than do the large bank portfolios. Reinganum and Smith (1983) have pointed out that for this differential information explanation to hold, the additional risk caused by the relative lack of information must not be idiosyncratic. That is, the lack of information must be a source risk that cannot be diversified away.

3.6 Difference between the jump-diffusion model and the CAPM

How distinct is the jump-diffusion model from the conventional CAPM? Existing tests on model specification find in favour of jump-diffusion model. However, here we formally test whether jump-diffusion model is related to the CAPM. Since the jump diffusion model can be written as

$$r_{i,t} = r_{m,t}[(1-\emptyset)\beta_{i,t}^{c} + \emptyset\beta_{i,t}^{j}] \tag{3.9}$$

Equation (3.9) can be used to construct a test based on whether the beta in the conventional CAPM is the weighted average of the jump beta and diffusion beta in the jump diffusion model. The hypothesis therefore is

$$H_0: \beta_{i,t}^{S} = [(1-\emptyset)\beta_{i,t}^{c} + \emptyset\beta_{i,t}^{j}] \tag{3.10}$$

The hypothesis can be tested with the following regression model

$$\beta_{i,t}^{S} = c_0 + c_1\beta_{i,t}^{c} + c_2\beta_{i,t}^{j} + \epsilon_{i,t} \tag{3.11}$$

The testable hypothesis is

$$c_1 + c_2 = 1 \tag{3.12}$$

Table 3.8: Testing distinction between the jump-diffusion model and the CAPM

H0: Test whether the beta in conventional CAPM is the average of diffusion beta and jump beta in the jump-diffusion model						
H0: C1+C2=1						
Panel A: Individual Stocks						
	OLS	**5th quant**	**25th quant**	**50th quant**	**75th quant**	**95th quant**
F-stat	18.63***	172.21***	47.85***	1.71	8.5**	18.07***
P-value	0.000	0.000	0.000	0.192	0.004	0.000
Panel B: Portfolios						
	OLS	**5th quant**	**25th quant**	**50th quant**	**75th quant**	**95th quant**
Small	17.77***	91.04***	29.56***	8.82***	21.77***	8.45***
	0.001	0.000	0.000	0.003	0.000	0.004
2	3.69	67.95***	11.08***	7.82***	0.78	18.94***
	0.065	0.000	0.001	0.005	0.379	0.000
3	1.55	23.2***	6.63***	0.05	0.00	0.82
	0.225	0.000	0.010	0.827	0.960	0.364
4	14.8***	63.99***	56.38***	38.84***	27.01***	8.59***
	0.001	0.000	0.000	0.000	0.000	0.004
High	114.88***	74.26***	20.38***	49.41***	64.65***	37.35***
	0.000	0.000	0.000	0.000	0.000	0.000

Note: The table presents F-test for testing whether the beta in the conventional CAPM is the weighted average of the jump beta and diffusion beta in the jump-Diffusion model. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

In Table 3.8, we report the results of the F-test for whether the systematic risk is a weighted average of diffusion and jump betas. In Panels A and B of Table 3.8, the F-tests do not reject the hypothesis in the conditional median distribution that the conventional CAPM is a weighted average of diffusion and jump betas. Our empirical findings agree with the model in that on average the systematic risk on an asset is the weighted average of both jump and diffusion betas.

3.7 Conclusion

In this chapter, we applied a novel method based on categorising a security's systematic risk into two components, the diffusion beta and the jump beta to evaluate empirically whether there is relationship between standard beta, diffusion beta and jump beta across different banks and how these different betas behave across different banks. We employ a quantile regression model to investigate a more complex relationships with high frequency data.

Through a decomposition of the simple CAPM beta into two components (diffusion beta and jump beta) we show that we can increase our understanding of the types of risk that investors need to be compensated. Using the high-frequency data of the Japanese banks for the years of 2001-2012, we find that the relation between standard, diffusion and jump betas changes in magnitude across the distribution quantiles. More importantly, we find that standard beta is affected more by the diffusion beta than the jump beta, although the actual magnitude of the weights differ significantly across the quintiles. The relationship holds for both individual stocks and various test portfolios.

Empirical studies have shown that betas vary systematically for large and small firm equities. We provide some additional insights into the precise way in how the bank betas are related to size. A close look at our results indicates that on average large banks have large betas whereas small banks have small betas i.e. larger Japanese banks are more sensitive to both market movements than smaller institutions, regardless of whether they occur through a jump or not. However, the paper demonstrated that portfolios based on firm size exhibit the jump-diffusion beta ratio of small portfolio equities, the jump beta disproportionately is larger than its associated diffusion beta, indicating a possible size effect. The result suggests that information asymmetry could be more severe for small banks than large bank; accordingly, the systematic exposure of bank could be quite different for large banks than small banks.

In addition to analysing the behaviour of betas at different quantiles, this study makes a comparison between the jump-diffusion model and the conventional CAPM. Our test results shows that the systematic risk is equal to the weighted average of diffusion risk and jump risk, confirming the validly of our analysis.

Chapter 4

Links between Trading Volume, Beta Changes and Price changes-Evidence from the Japanese Banking sector

4.1 Introduction

Beta, as the sole measure of systematic risk according to the Capital Asset Pricing Model (CAPM), is one of the cornerstones of modern finance. Financial researchers as well as market participants rely on the beta coefficient to estimate cost of capital for capital budgeting and also to evaluate the performance of managers. The beta of a security represents the asset's sensitivity to movements in the market and is defined as the co-variance of the stock returns with the market returns. Beta, in the past has been generally assumed to be constant over time for quick and easy estimation.

However, it is currently considered an empirical fact that beta of a stock or portfolio is time varying and hence not constant (Bollerslev et al. 1988; Fabozzi and Francis 1978). A sizeable literature demonstrate that because market fundamentals are time varying Shiller et al. (1984), Lettau and Ludvigson (2001)), stock and portfolio betas change over time (see e.g. Bollerslev et al. (1988), Lettau and Ludvigson (2001)). Hence, time-varying beta is one definite source of beta uncertainty. The other source of beta uncertainty stems from estimation errors due to in the error in the estimates of security betas resulting from 'the inappropriate use of chronological time as an index in the return computation' (see (Carpenter and Upton 1981)). Using trading volume as an instrumental variable to index the speed of evolution of the return generation process, Carpenter and Upton (1981) find that trading volume has a significant influence on the estimated betas. The intuition is that high volumes indicate that the operational trading time is passing more rapidly than the chronological trading time and low volumes indicate that operational time is passing at a slower pace than the chronological time. This means that, for a fixed chronological period, high volumes imply the passage of comparatively more operational time (a longer operational time "period"). The same fixed chronological period with low volumes imply the passage of comparatively less operational time (a shorter operational time "period"). Hence, to the extent the market return proxy is incorrectly specified (i.e. as chronological time and not as operational time), the ensuring beta estimates will be less accurate and hence more uncertain. The result of this reduced accuracy will be a wider standard deviation for the distribution in beta estimates over time conditional on trading volume.

The estimation error is a direct consequence of the speed of information flow i.e. the speed in 'the processing of information about the effect of systematic news on firm value' (see Gilbert et al. (2014)). High volumes imply fast dissemination of information and low volumes imply a slow dissemination of information. Moreover, Blume et al. (1994) argue that volume provide information on the precision and dispersion of information signals to market that cannot be observed from price alone.

This chapter investigates the linkages between beta changes and trading volume for Japanese banks stocks on the Tokyo stock exchange (TSE). An investigation of the TSE is of interest for two main reasons. First, the evidence on links between beta changes-volume (and price changes-volume) relationship is mainly from the US market; see, for example, Ciner (2015). However, as to whether the findings for the US market can be generalized to other markets, with a different microstructure, is an unresolved question. Second, the Japanese capital market is unique because the institutional setup of the Tokyo Stock Exchange (TSE) is significantly different from the commonly analyzed US equity exchange, including lunch breaks, with a batched trading process, *Itayose*, used to clear orders at the start of each trading session, followed by a continuous auction. *Zaraba* for the rest of the session. The actual trading on the exchange is done by specialized security houses, i.e. *Saitori* members who are responsible for matching the orders without taking positions themselves. For more details, see, Amihud and Mendelson (1991), Lehmann and Modest (1994), Hamao and Hasbrouck (1995), and Andersen et al. (2000).

The empirical analysis begins with an examination of the relationship between monthly trading volume and changes in betas. Our main empirical results are based on monthly standard, diffusion and jump beta estimates for each of the stocks in the sample.[31] We study the linkages between trading volume and beta changes (and price changes) using quantile regressions in addition to the conventional ordinary least squares (OLS). While the classic linear regression model only describes the conditional mean, the quantile regression describes the complete picture of the conditional distribution of the dependent variable. The quantile regression has thus the potential to uncover asymmetric relations, if any, between the variables exhibited at the extremities of the distribution.

Using high frequency Japanese banks stock data from 2001–2012, we find that there is a statistically significant relation between trading volume and changes in betas.[32] Despite the OLS conditional regression suggesting a homogeneous relation between volume and changes in standard, diffusion and jump betas, there are strong evidences of an asymmetric beta-volume relation from the quantiles regression. We find a positive relation between trading volume and changes in diffusion betas at lower quantiles while a negative beta-volume relation is found at higher quantiles. The same findings also hold for the relation between trading volume and changes in jump beta. Similarly to Carpenter and Upton (1981), we also find that trading volume does have an effect on the estimated betas. We also document the relationship between volume and changes in standard betas from lower quantiles to upper quantiles. The delta beta-volume relationship is asymmetrical with the lower quantiles being less positively sloped and the upper quantiles being very negatively sloped. The asymmetrical beta-volume relationship across the standard betas implies that the relation is fundamentally different for changes in standard beta, as when compared to diffusion beta or the jump beta.

Since the systematic risk, beta, is a function of price-changes (according to the CAPM), we also examine whether the observed non-linear linkages between beta and volume are analogously mirrored by the price and volume relationship**.** In this context, Llorente et al. (2002) have proposed a likely model to explain the relation between volume and price changes. The underlying intuition of their model is that market participants trade in the stock market either

[31] Our empirical results are based on diffusion, jump and standard betas estimated from high-frequency data for each of the individual stock in the sample. Estimates for diffusion, Jump and standard betas are computed on a month-by-month basis. High frequency data permits the use of 1-month non-overlapping windows to analyse the dynamics of our systematic risk estimates.

[32] It is widely agreed that in financial markets, trading activity induces price changes and trades directly contribute to price discovery. We are interested on how volume proxies for beta uncertainty (beta-changes) and thus we employed volume as proxy for information flow. Further, volume evolves month to month, whereas, size does not evolve month to month. Since size is relatively time invariant, it will not provide a useful proxy for volume.

to hedge and share risk (i.e. uninformed traders) or to speculate on private information (i.e. informed traders). If hedging (or liquidity) is the primary motive to trade, negative autocorrelation will be observed. That is because investors sell a stock for hedging reasons, and the stock price decreases, yielding a negative return for that period since the expectation for the future payoff stays the same. The drop in the price leads to a high expected return for the next period. However, if speculation is the primary motive to trade, positive autocorrelation will be observed. That is because investors sell stock due to the arrival of negative information, the stock price decreases, yielding a negative return for that period. Since the price only partially reflects the negative information, the return in the current period will be followed by a low return in the next period as the negative information become public.

From the above considerations, Gebka and Wohar (2013) argue that the following picture of the price-volume nexus emerges. If speculation on positive private information is the primary motive to trade, one should observe a positive price-volume relation and the price-changes will likely be from higher quantiles today with increased trading volume. This is exactly the pattern that this chapter reveals. A similar implication holds if selling pressure for hedging (due to liquidity reasons) dominates the market, i.e. trading from hedging pressure will generate high volume and will drive the price down in order to attract other investors to buy. However, the stock price will bounce back to its fundamental value in the next period for the market to accommodate the buying pressure, generating returns likely from the higher quantiles. Therefore, a positive price-volume relation will be observed from higher quantiles. If, on the other hand, intensive trading from hedging pressure to buy, the next period return will likely be from lower quantiles, since there will be a decline in price back to the fundamental value, generating a negative link between price changes and trading volume from the lower quantiles. Lastly, trading on negative private information will induce high volume and negative returns in the current period followed by negative returns in subsequent period, a negative causality from volume to return will be observed from lower quantiles since it will take more than one period for the negative information to be incorporated into pricing.

In light of the above model, this paper then investigates the nature of the price-volume relationship using the quantile regression approach employed in Chapter 3. We establish a significant price-volume relation, which emphasize their central role of volume in price-changes. We show a positive (negative) price-volume relation at high (low) quantiles. This finding is consistent with Ciner (2015), Gebka and Wohar (2013) and Chuang et al. (2009), who find that trading volume exerts a positive (negative) impacts on price-changes or returns from the top (bottom) quantiles of the observed return distribution. Our empirical results are entirely consistent with the equilibrium model by Llorente et al. (2002), who show that the impact of the information revealed by volume on price behavior can be complex, depending on the nature of the information.

The chapter is organized as follows. Section 4.2 discusses the methodology. Section 4.3 presents the data. Section 4.4 contains the empirical results. Section 4.5 concludes.

4.2 Methodology

We use quantile regression models to investigate the beta-volume relationship as well as price-volume relationship for the Japanese banks. First we investigate whether trading volume has explanatory power for changes in betas if we distinguish standard betas into diffusion and jump betas. The framework for distinguishing jump and diffusion betas in individual asset prices consists of two parts. First, a univariate jump detection test is applied to determine days where jumps occur. This selects the jump days to be considered in the second stage which uses ratio statistics to determine the estimates of the two betas for each stock. We follow the process of Todorov and Bollerslev (2010) and apply the Barndorff-Nielsen and Shephard (2006) jumps test in the first stage.

4.2.1 Standard, diffusion and jump betas

We begin the analysis by estimating realized betas using the method illustrated in Andersen et al. (2006). The advent of readily available high frequency data in recent years, have now made it possible to compute realized betas over varying frequencies that can be used as proxies for standard betas.

Realized beta is defined as the ratio of realized covariance of stock and market to the realized market variance. Andersen et al. (2006) argue that realized beta is a more accurate measurement of the standard beta because it employs more information than the traditional regression on monthly returns.

The estimate of realized beta for individual stock, $\hat{\beta}_{i,t}^{s}$ is defined as:

$$\hat{\beta}_{i,t}^{s} = \frac{RCOV_{i,t,s}^{s}}{RV_{m,t,s}^{s}} = \frac{\sum_{s=1}^{n} r_{i,t,s}\, r_{m,t,s}}{\sum_{l=1}^{n} \left(r_{m,t,s}\right)^{2}} \tag{4.1}$$

where $r_{i,t.k}$ is the return on stock i during the k^{th} intraday period and $r_{m,t,s}$ is the aggregate market return at time t, and S is the number of intraday periods. This estimator was studied by

Todorov and Bollerslev (2010) in the presence of jumps. The CAPM model basically depends on returns in the individual stock and the market, which in turn, depend on the underlying prices of individual stocks.[33]

For our analysis, we consider the presence of jumps in the price process and rely on Barndorff-Nielsen and Shephard (2006)'s framework to detect the jump in the price process. In the presence of jumps, Todorov and Bollerslev (2010) provide a theoretical method for decomposing the time-varying beta for stocks into beta for diffusion systematic risk and beta for jump systematic risk. Following Todorov and Bollerslev (2010), we decompose the CAPM beta into a part attributable to a diffusion component-diffusion beta and a part attributable to jumps-jump beta. In the most general case, each of the factor components has a separate loadings (diffusion and jump), and when these two loadings are equal, the model simplifies to a standard one-factor model. The first step in our analysis is to test for the presence of a jump in the market price on each day, and we do so using the "ratio" jump test of Barndorff-Nielsen and Shephard (2006), sampling frequency (five minutes), and critical value (3.09). On days with no jumps in the market, the usual realized beta is an estimate of the diffsuion beta. On days with jumps in the market, one can use the estimator in Todorov and Bollerslev (2010) to estimate the jump and diffusion betas separately.

4.2.2 Quantile regression methodology

In this section we present the quantile regression model to examine the relationship between volume and beta changes (and price change). Following Koenker and Bassett (1978), we use the QR technique to examine whether the beta-volume (price-volume) relation studied changes across the quantiles of the conditional beta (price) distribution. The quantile regression model allow us to estimate the relationship between a dependent and explanatory variables at any specific quantiles, while ordinary least squares (OLS) regression focuses on the estimation of the conditional mean of the dependent variable. The OLS method would come to the conclusion that in spite of potentially different relationships at different quantiles, the various economic factors affect the relation in exactly the same way. If there is variability in the effects across the distribution it will not captured by the OLS method. The literature shows that the linkages at the extreme, very high or low quantiles, can differ from the mean relationships. In other words, trading volume may impact the betas at quantiles other than the means. It is also well

[33]It is now widely agreed in the literature that financial return volatilities and correlations are time-varying and returns follow the sum of a diffusion process and a jump process. See, for example, Press (1967), Merton (1976), Ball and Torous (1983) and among others.

known that outliers may have a much larger effect on the mean of distribution than to the median. Thus, quantile regression methodology may provide a better picture than OLS regressions even for the medium of the distribution.

The quantile regression takes the following form:

$$y_i = x'_i . b^\tau + \varepsilon_i^\tau \tag{4.2}$$

$$Quant_\tau(y_i|x_i) \equiv inf\{y: F_i(y|x)\tau\} = x'_i . b^\tau$$

$$Quant_\tau(\varepsilon_i^\tau|x_i) = 0$$

where $Quant_\tau(y_i|x_i)$ denotes the τ th conditional quantile y_i on the regression vector of the x_i. The parameter vector b^τ is associated with the τ-quantile while ε_i^τ is the error term assumed to be continuously differentiable c.d.f. (cumulative density function) of $F_\varepsilon^\tau(.|x)$ and a density function $F_\varepsilon^\tau(.|x)$. The $F_i(.|x)$ denotes the conditional distribution of y conditional x. Varying the value of τ from 0 to 1 reveals the entire distribution of y conditional x. Note that the local effect of x_i on the τ-quantile is assumed to be linear. The slope coefficient vector b^τ differs across quantiles and the estimator for b^τ is obtained from

$$min \sum_{i:\varepsilon_i^\tau>0} \tau \times |\varepsilon_i^\tau| + \sum_{i:\varepsilon_i^\tau<0} (1-\tau) \times |\varepsilon_i^\tau|$$

$$= \sum_{i:y_i - x'_i\beta^\tau \geq 0} \tau \times |y_i - x'_i b^\tau| + \sum_{i:y_i - x'_i\beta^\tau < 0} (1-\tau) \times |y_i - x'_i b^\tau| \tag{4.3}$$

The quantile function is estimated by minimizing a weighted sum of absolute residuals, where the weights are functions of the quantiles of interest. The value of b for any τth regression quantile can be estimated by linear programming methods. For more details, see, Koenker (2005).

4.3 Sample and data

Our sample consists of 5-minute transaction prices and monthly trading volumes from January 2001-Deccember 2012.[34] The 5-minute transaction price data are obtained from Thompson Reuters Tick history (TRTH) database extracted using via SIRCA and trading volume data are obtained from Datastream database. We use the Nikkei 225 index as a proxy for the market

[34] The sampling frequency of 5 minutes is relatively standard in the high frequency literature, posing a reasonable compromise between the need to sample at very high frequencies in order to resemble the continuous price process (Bollerslev et al. 2009), and possible contamination from micro-structure noise.

portfolio in calculation of standard betas, diffusion betas and jump betas. We rely on a fixed intraday sampling frequency of 5-minute returns in our estimation of the standard, diffusion and jump betas. The final sample consists of high frequency stock price data for 50 of the 63 commercial banks traded on the Tokyo Stock Exchange (TSE).[35] Data were not available for the whole sample period for the remaining 13 banks. Following Gallant et al. (1992), Hiemstra and Jones (1994), Chuang et al. (2009) and more recently Ciner (2015) we use the logarithmic of monthly number of shares traded, as our measure for trading volume.

4.4 Empirical results

4.4.1 Trading volume and beta changes

We investigate the relation between changes in betas and trading volume for the Japanese banking stocks. We consider the following model, where $\Delta\beta_{i,t}$ (Δbeta) stands for monthly changes in betas calculated as $(\beta_{i,t} - \beta_{i,t-1})/\beta_{i,t-1}$, by OLS:

$$\Delta\beta_{i,t} = a_0 + b_i Vol_{i,t} + \varepsilon_{i,t} \tag{4.4}$$

The variable of primary interest is the coefficient of trading volume on the three different Δbetas, namely changes in standard betas, diffusion betas and jump betas. We present the regression results in two tables. Table 4.1 presents results of entire sample and Table 4.3 (in the Appendix) reports the results for individual banks over the entire sample period.

In Table 4.1, the three delta betas are the dependent variables and volume is the independent variable. The OLS results show that for jump betas and standard betas, the coefficient of trading volume is not significantly different from zero. However, this is not case for the diffusion betas. Results from Table 4.1 show the positive and statistically significant effect (at 5% level) of the trading volume on diffusion betas. Moreover, the results are qualitatively similar when we run the regression Equation (4.4) for each individual stock.

[35] Unlike the NYSE, the trading hours of the Tokyo Stock Exchange span two sessions on any trading days, from 9:30 AM to 11:30 AM and from 12:30 PM to 3:00 PM with a short lunch break in between. Paralleling many previous studies, we use five-minute intervals as the sampling frequency to strike a reasonable balance between accurate measure and microstructure noise. Missing data at 5-minute intervals are filled with the previous price creating a zero return. Hansen and Lunde (2006) show that this previous tick method is a sensible way to sample prices in calendar time. Since there are no transaction records in the first 5-minute interval of many trading days, and also to avoid opening effects, our dataset spans 09:05–11:30 and 12:35–15:00 on each working day (excluding weekends, public holidays and firm-specific trading suspensions) from January 2, 2001 to December 27, 2012. Overnight and over-lunch returns are excluded from the data set. We are only concerned with the active trading period, and overnight information is beyond the scope of this study.

Table 4.3 shows that the majority of the companies have a positive relation on average between changes in diffusion betas and trading volume. A mixed finding holds when the jump beta is used as the dependent variable. However, estimation results for standard betas, provided in Panel C of Table 4.3, show that a majority of companies display negative coefficient estimates. Furthermore, the coefficients are rather small in each case, which makes it difficult to interpret the economic significance of the relation between beta variation and trading volume.

Table 4.1: Beta changes and trading volume: contemporaneous relations

Dependent Variable= Delta Diffusion Beta						
	OLS	Q05	Q25	Q50	Q75	Q95
Volume	0.116***	0.454***	0.201***	0.078***	-0.011	-0.274***
	(0.017)	(0.058)	(0.011)	(0.007)	(0.012)	(0.048)
Constant	-1.206***	-6.491***	-2.452***	-0.870***	0.415***	4.584***
	(0.152)	(0.556)	(0.117)	(0.066)	(0.115)	(0.483)
Dependent Variable= Delta Jump Beta						
Volume	0.022	0.340***	0.074***	0.029***	-0.042***	-0.278***
	(0.015)	(0.024)	(0.006)	(0.007)	(0.013)	(0.024)
Constant	-0.184	-4.454***	-1.003***	-0.308***	0.703***	4.008***
	(0.146)	(0.273)	(0.056)	(0.065)	(0.118)	(0.250)
Dependent Variable= Delta Standard Beta						
Volume	-0.018	0.098***	0.041***	0.005	-0.047***	-0.274***
	(0.013)	(0.010)	(0.004)	(0.003)	(0.006)	(0.025)
Constant	0.268**	-1.501***	-0.609***	-0.063**	0.703***	3.829***
	(0.125)	(0.103)	(0.040)	(0.032)	(0.062)	(0.264)

Note: OLS regression results from Equation (4.4) and depicts the contemporaneous relation between trading volume and beta-changes. Quantile regression estimates are from Equation (4.5) and test the contemporaneous relation between variables at specific quantiles. **Standard errors** are displayed in parentheses below the **coefficients**. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

We also investigate whether there is a lagged relation between trading volume and betas. We run the same OLS regression in Equation (4.4) including lagged volume. Information spillovers from lagged trading volume to betas can exist if the adjustments to new information in the market is gradual rather than contemporaneous, which would be consistent with the sequential information arrival. The regression results are reported in Tables 4.2 and 4.4 (in the Appendix). As with the contemporaneous results, in Table 4.4 we find a positive relation between the changes in diffusion betas and volume for most of the companies in our sample.

Table 4.2: Beta changes and lagged-trading volume

	OLS	Q05	Q25	Q50	Q75	Q95
Dependent Variable= Delta Diffusion Beta						
Lag volume	0.117***	0.472***	0.198***	0.077***	-0.011	-0.269***
	(0.017)	(0.050)	(0.012)	(0.007)	(0.011)	(0.050)
Constant	-1.214***	-6.652***	-2.425***	-0.855***	0.410***	4.487***
	(0.149)	(0.460)	(0.118)	(0.070)	(0.109)	(0.468)
Dependent Variable= Delta Jump Beta						
Lag volume	0.015	0.324***	0.075***	0.0325***	-0.038***	-0.293***
	(0.015)	(0.020)	(0.006)	(0.006)	(0.010)	(0.024)
Constant	-0.132	-4.291***	-1.014***	-0.334***	0.669***	4.165***
	(0.144)	(0.229)	(0.052)	(0.057)	(0.098)	(0.249)
Dependent Variable= Delta Standard Beta						
Lag volume	-0.016	0.097***	0.042***	0.005	-0.046***	-0.281***
	(0.013)	(0.008)	(0.004)	(0.004)	(0.007)	(0.026)
Constant	0.248*	-1.500***	-0.626***	-0.062*	0.702***	3.894***
	(0.124)	(0.074)	(0.040)	(0.036)	(0.065)	(0.264)

Note: OLS regression results from Equation (4.4) and the relation between beta-changes lagged trading volume. Quantile regression estimates are from Equation (4.5) and test the lagged relation between the variables at specific quantiles. **Standard errors** are displayed in parentheses below the **coefficients**. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

In Table 4.2 we also observe that the effect of lagged trading volume on changes in diffusion beta is statistically significant in comparison with Table 4.1 and the signs are consistent with expectations. Conversely, trading volume does not have a statistically significant impact on changes in standard betas and jump betas.

The OLS regressions conducted above examine the average relationship between the variables. However, recent research points out that the relationship between the variables may differ significantly across the quantiles of the response variable, with stronger asymmetry potentially revealed in the low/upper quantiles. Put differently, trading volume may have different impacts on the betas at the quantiles other than the mean. To help further gauge this effect, QR analysis used in this paper to investigate the relation between beta changes and trading volume at selected quantiles of the distribution of the former, not just the mean as the OLS provides.

We proceed to examine the contemporaneous relations between monthly beta changes and trading using the following quantile regression model:

$$Q(\tau)_{\Delta\beta}\ (\Delta\beta_{i,t}) = a_0(\tau) + b_i(\tau)Vol_{i,t} + \varepsilon_{i,t} \tag{4.5}$$

The slopes of the regressors are estimated at five different quantiles τ −the 5th, 25th, 50th, 75th, 95th- using the same set of explanatory variables for each quantile. The results are also reported in Tables 4.1 to 4.4. The results exhibit a statistically significant relation between changes in diffusion beta and trading volume in at least one of the quantiles. In the higher quantiles of 0.95 and 0.75, the relationship is negative, while the relationship is found to be positive in lower quantiles of 0.05 and 0.25. We also estimate Equation (4.5) for each bank in our sample. We find that the majority of the coefficient estimates for b_i are largely negative and statistically significant in higher quantiles of 0.95 and 0.75, whereas more positive coefficient estimates are obtained in lower quantiles of 0.05 and 0.25. The same finding holds when the changes in jump beta are used as the dependent variable.

When we consider the effect of trading volume on the changes in standard beta and for the standard beta, the picture is same. The results indicate that the changes in standard beta and trading volume are statistically and negatively related in upper quantiles, while they are statistically and positively related in lower quantiles. We also find the similar pattern for majority of banks in our sample. This finding is consistent with Ciner (2015), who find that large increases in systematic risk (standard beta) tend to be positively associated with trading volume.

As discussed in Section 4.2.2, whereas the OLS estimates only capture the beta-volume relationship in the mean, the results from quantile regression provide a complete picture of beta-volume relation across the whole distribution (or at selected quantiles) and not just at the point of central tendency (i.e. the mean). The quantile regression plots for each independent variable with their respected significance ranges are presented in Figure 4.1 which plots τ against the QR estimates of $b_i(\tau)$ (solid line) and their 95% confidence intervals (in shaded area), together with the OLS estimate as the dashed horizontal line and its 95% confidence interval in the dotted lines for the model with contemporaneous relations between beta-volume. The plots clearly show why the conditional mean does not fully characterize (the asymmetric) beta-volume relation.

It can be seen that for jump betas, the OLS estimates of b_i is not significantly different from zero, suggesting that, on average, trading volume is not a determinant of variation in jump betas. For the diffusion betas, the OLS estimates of b_i is significantly positive at the 1% level. On the other hand, the QR estimates of $b_i(\tau)$ for the three betas vary with quantiles and exhibit a distinct and curved pattern. The QR estimates are positive at lower quantiles and negative at upper quantiles. The QR estimates are also significant at both lower quantiles and upper quantiles. Thus, trading volume has an impact on changes in all the betas and such effects are stronger at more extreme quantiles.

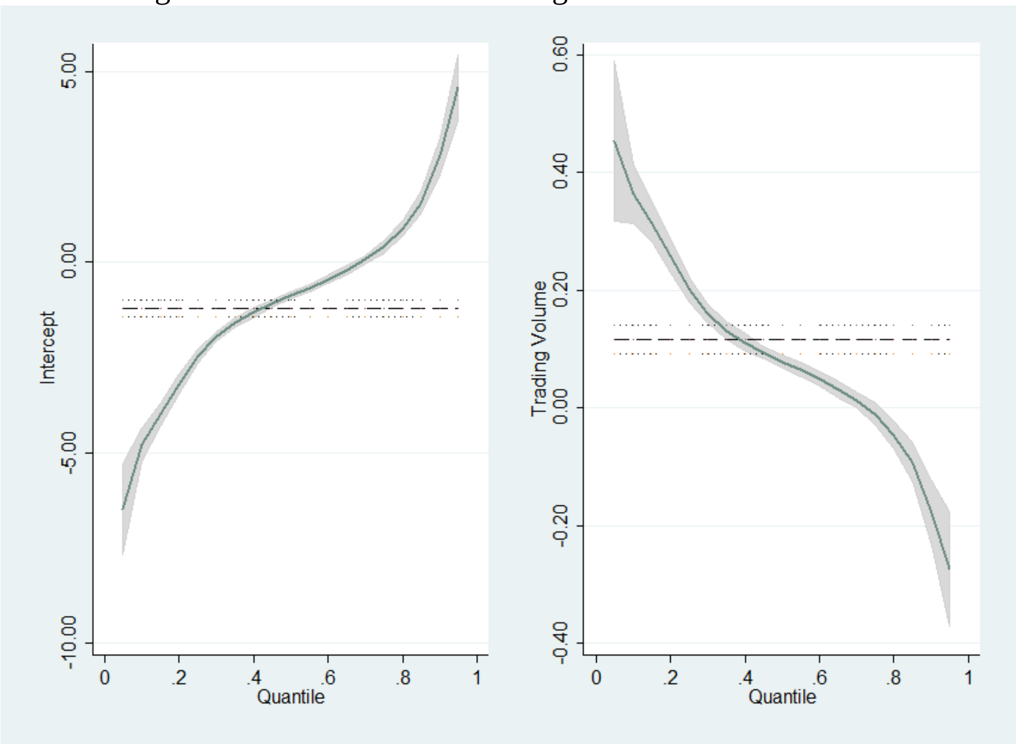
The estimation results for standard beta are quite different as shown in panel C of Figure 4.1. The OLS estimates of b_i is negative but insignificantly different from zero but that of non-central $b_i(\tau)$ is significant. The QR estimates of $b_i(\tau)$ are also heterogeneous across τ. The QR estimates of $b_i(\tau)$ are significantly positive at lower quantiles and significantly negative at upper quantiles. Figure 4.2 plots the QR and OLS estimates for model with lagged relation in all betas. The results are similar to the previous results from Figure 4.1.

We can further illustrate the difference between least squares regression and quantile regressions using a Δbeta-volume scatter plots. Figure 4.3 (and Figure 4.4) shows the scatter plots between the changes in betas and trading (and lagged) volume for the Japanese banks. These plots form a cone or comet shape, suggesting that as trading volume increases, changes in betas display a greater range of concentration (i.e. less variation). In Figures 4.3 and 4.4, we present the quantile regression lines labelled $\tau = 5^{\text{th}}$, 25^{th}, 50^{th}, 75^{th}, and 95th, respectively. The quantile regression lines labelled 0.05 and 0.25 fall below the mean/median lines, presenting a positive slope, while the regression lines labelled 0.95 and 0.75 quantiles lie above the mean/median lines, showing a negative slope. The beta-volume relationship transforms from positive to negative as the quantile increases.

Overall the quantile regression results show the significant impact of the trading volume on changes in betas, at least in the off-central quantiles, contrary to the insignificant OLS-based results, stressing the fact that the relationship may be far more complex than what can be described using least-squares regression. Indeed, the beta-volume relationship for Japanese banking stock is asymmetric and the relationships at the tail quantiles are quite different from that at the mean. The results show that trading volume is indeed a determinant of variation in Δbetas.

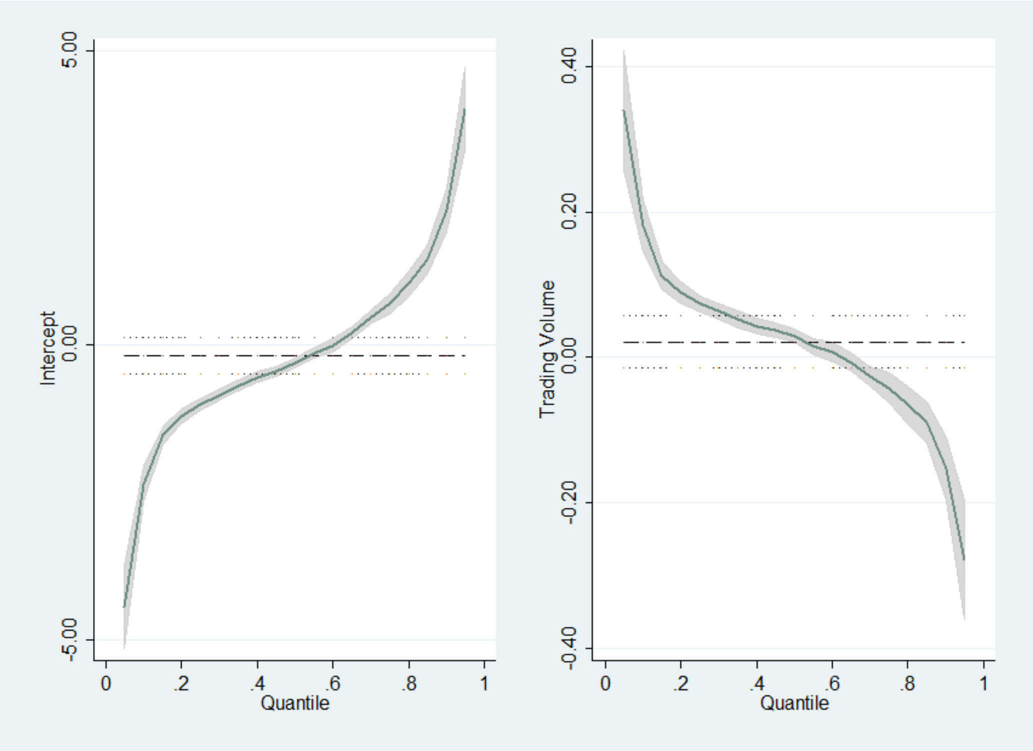
Figure 4:1: QR and OLS estimates of the effects of trading volume on beta changes: contemporaneous relation

Panel A: Changes in diffusion beta and trading volume



Note: The solid line gives the coefficients of trading volume estimates from the quintile regression, with the shaded grey area depicting a 95% confidence interval. The dashed line gives the OLS estimate of mean effect, with two dotted lines again representing a 95% confidence interval for this coefficient

Panel B: Changes in jump beta and trading volume



Panel C: Changes in standard beta and trading volume

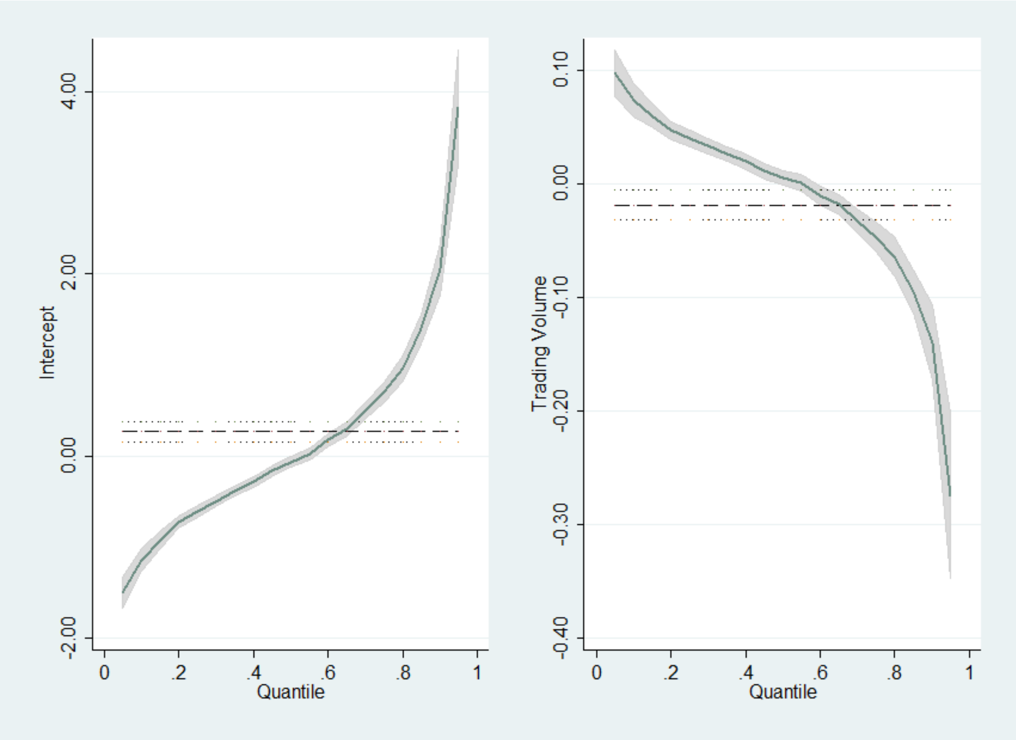
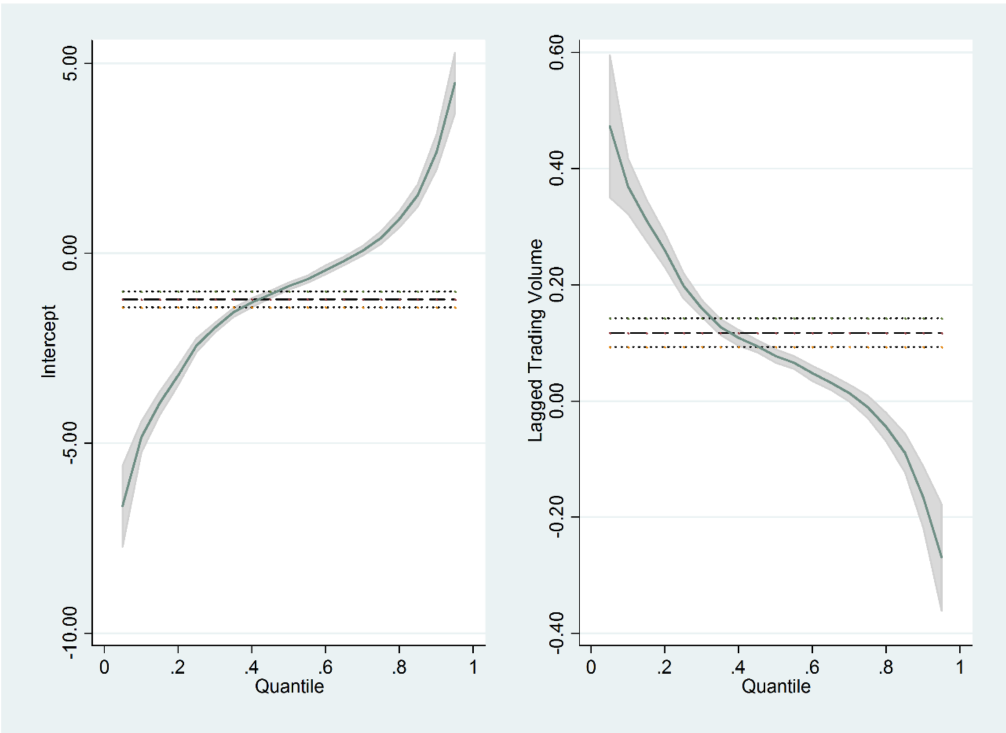
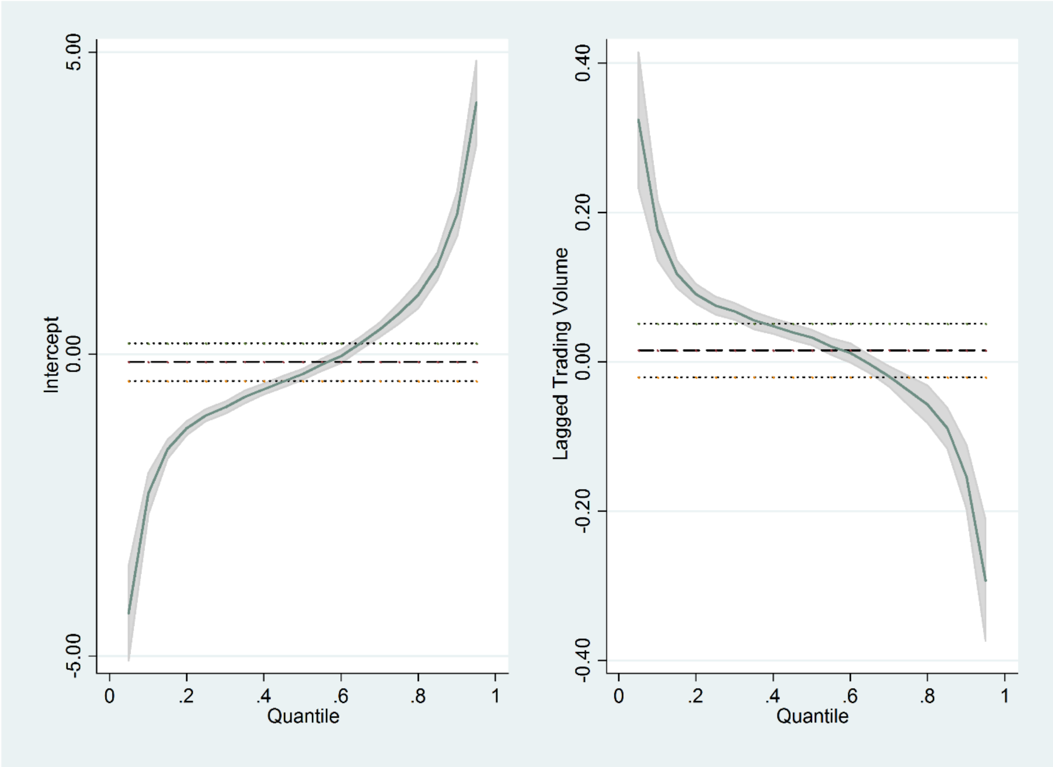


Figure 4:2: QR and OLS estimates of the effects of trading volume on beta changes: lagged relation

Panel A: Changes in diffusion beta and lagged trading volume



Panel B: Changes in jump beta and lagged trading volume



Panel C: Changes in standard beta and lagged trading volume

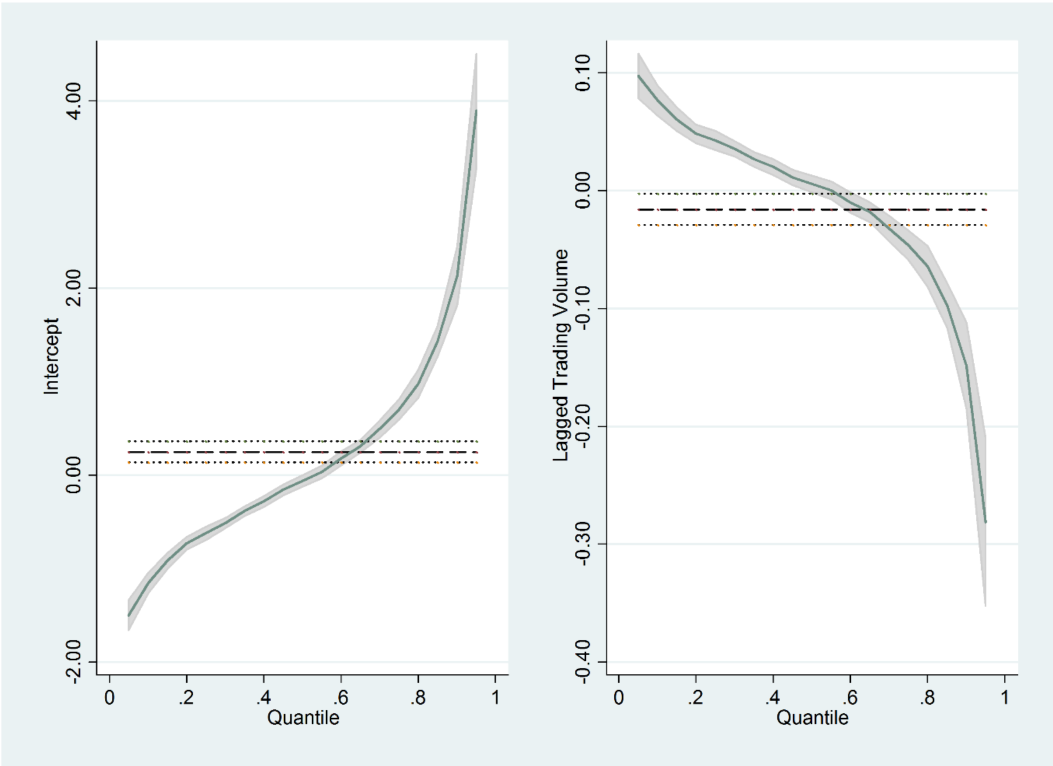
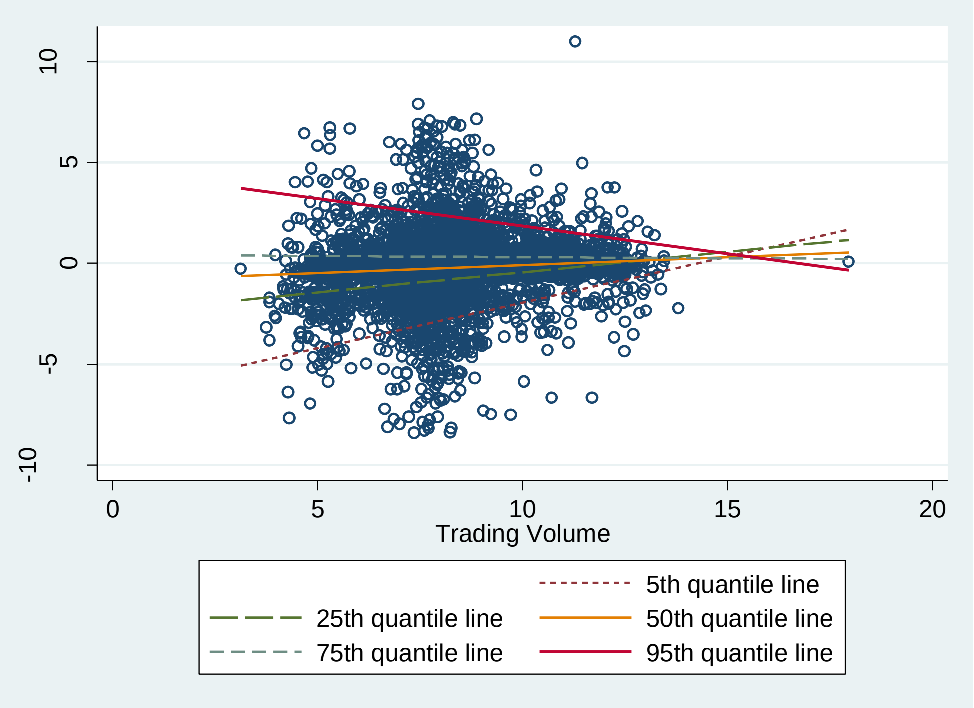
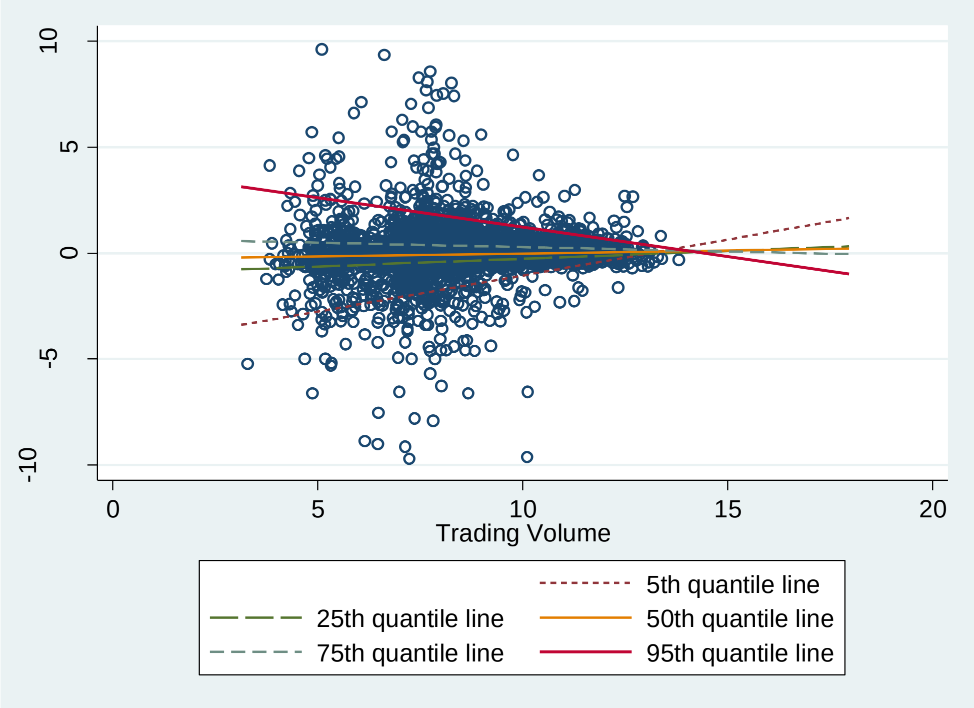


Figure 4:3: Scatter plot of changes in betas with trading volume for individual companies
panel a: changes in diffusion beta and trading volume



Panel B: Changes in jump beta and trading volume



Panel C: Changes in standard beta and trading volume

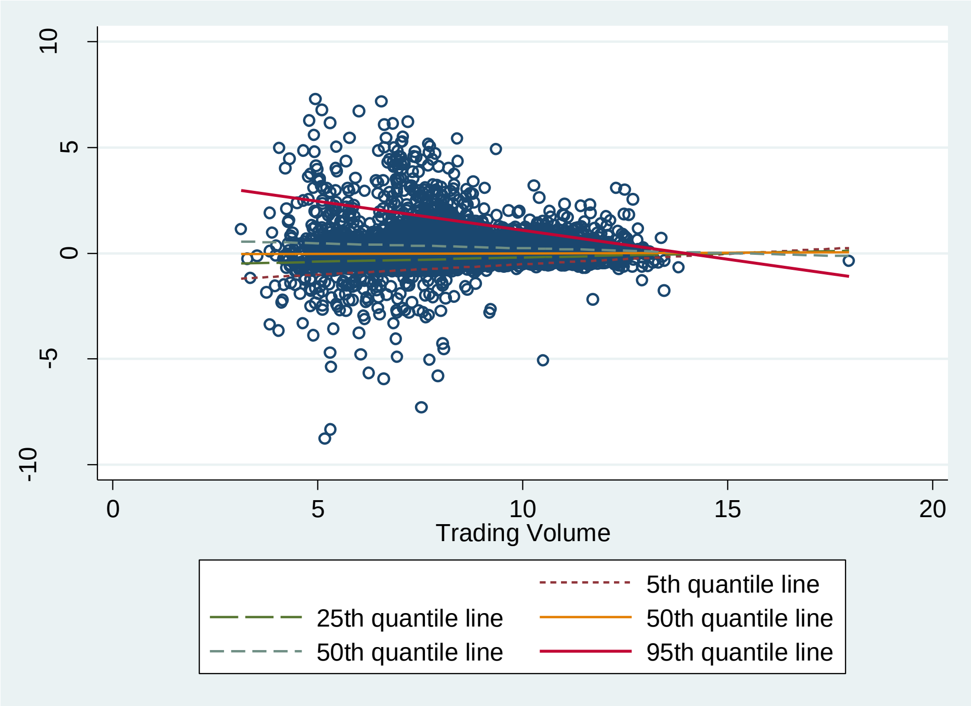
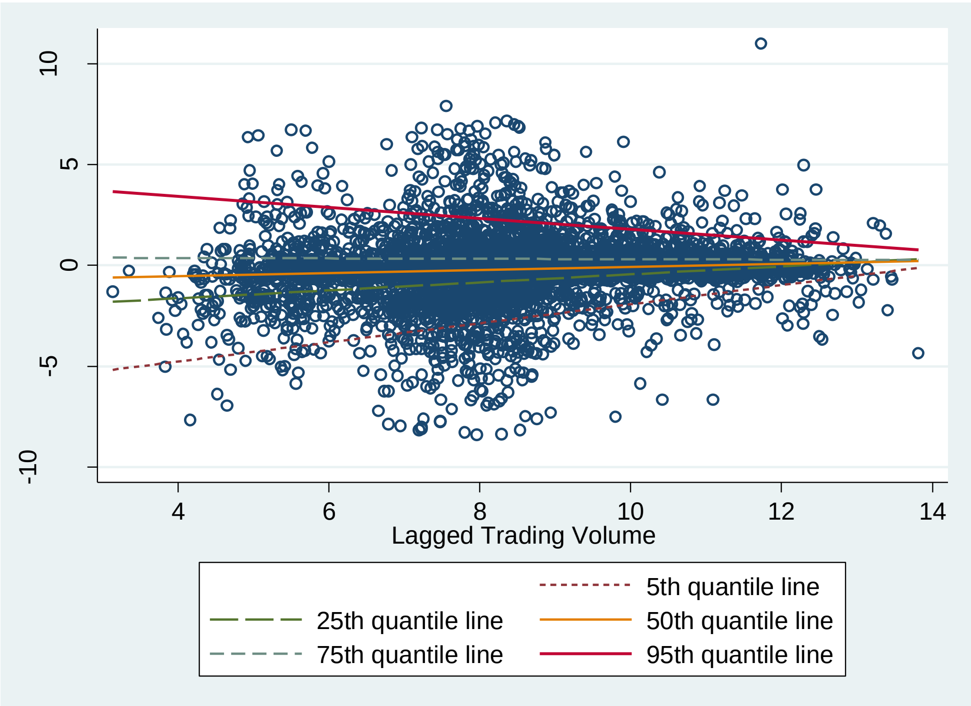
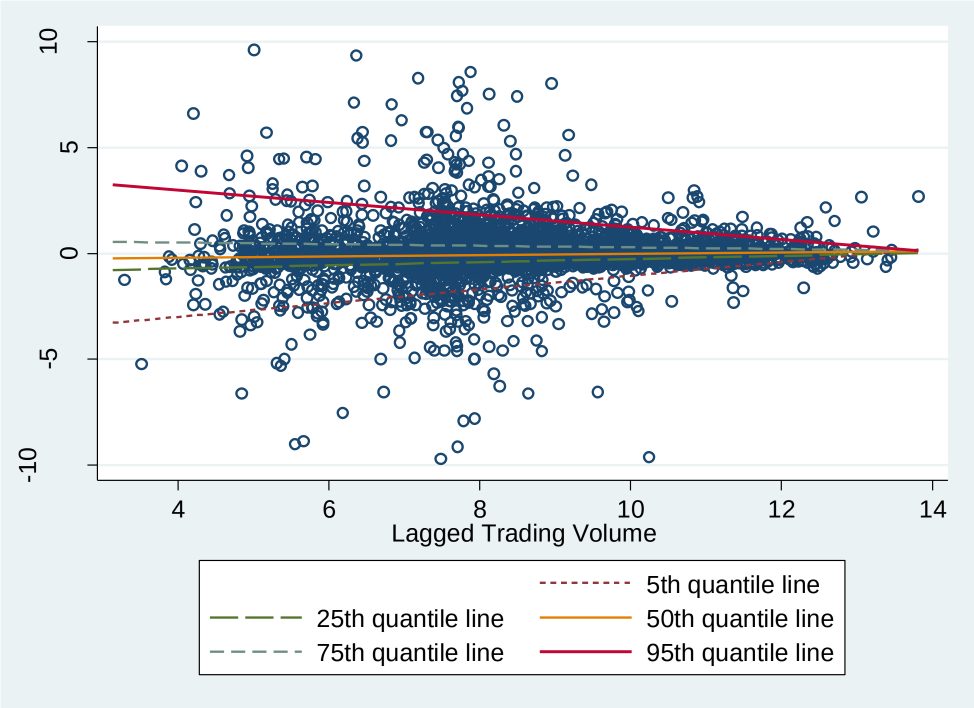


Figure 4:4: Scatter plot of changes in betas with lagged trading volume for individual companies

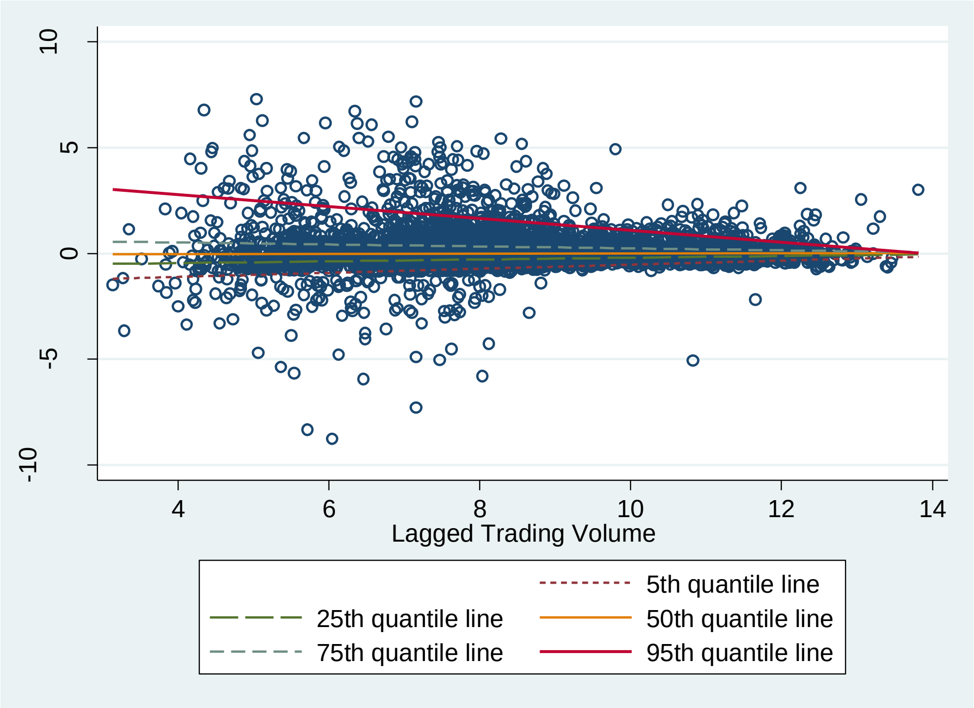
Panel A: Changes in diffusion beta and lagged trading volume



Panel B: Changes in jump beta and lagged trading volume



Panel C: Changes in standard beta and trading volume



Using quantile regression, we find that trading volume has a positive (negative) relationship with beta changes at lower (higher) quantiles. Further, we observe that stocks with high trading volume are associated with small beta changes. Conversely, stocks with low trading volume are associated with large beta changes; see Figures 4.3 and 4.4. Thus, stocks with higher trading volume have smaller Δbetas, i.e. low beta uncertainty and stocks with lower trading volume has larger Δbetas, i.e. high beta uncertainty. Our results support the view that changes-in- beta i.e. beta uncertainty, stem from beta estimation error due to time-varying volume or 'the inappropriate use of chronological time as an index in the returns computation'. See Carpenter and Upton (1981).

4.5 Volume and return

It could be argued that dynamic linkages between trading volume and changes in betas that documented above should be observed between price-changes and trading volume as well if CAPM is to have empirical consistency. Based on this intuition we proceed to investigate whether volume contains information on price changes. In the first part of the empirical analysis, we consider the following model for examining the contemporaneous relation between price-changes (or returns) and trading volume and estimate the model using the OLS and quantile regression methods:

$$R_{i,t} = a_0(\tau) + b_i(\tau)Vol_{i,t} + \varepsilon_{i,t} \tag{4.6}$$

Where $Vol_{i,t}$ is (log) trading volume and $R_{i,t}$ is (log) price changes. Although we may specify different models for the conditional mean and quantile functions, we estimate the same model (6) in our study so that the OLS and QR estimates can be compared directly.

Table 4.5 (below) and Table 4.6 (Appendix) present the results for the contemporaneous price-volume relationship. The results from OLS regressions in panel A of Table 5 indicate that price-changes do not have a statistically significant relationship with trading volume. We also estimate the contemporaneous price-volume relation using Equation (4.6) for each of stock in our sample. See Panel A of Table 4.6 (Appendix). We find that "a" majority of coefficients for b_i are negative but statistically insignificant. This finding is consistent with earlier work, in which researchers generally find that price-changes do not co-vary with trading volume, see Karpoff (1987) for a survey, and Lee and Rui (2002), Ciner (2002) and Ciner (2015) for some recent empirical evidence. This is generally regarded counter to the notion of financial market practitioners mantra that 'it takes volume to make prices move' (in Karpoff (1987)) and also, to the implications of models by Blume et al. (1994) and Llorente et al. (2002), who argue that volume carries information that is not contained in price statistics.

Table 4.5: Price chamges and trading volume

Panel A: Trading volume and return: contemporaneous relations

Dependent variable= Return						
	OLS	**Q05**	**Q25**	**Q50**	**Q75**	**Q95**
Volume	-0.001	-0.007***	-0.005***	-0.002**	0.001	0.006***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.004	-0.057***	0.002	0.012**	0.033***	0.061***
	(0.008)	(0.014)	(0.006)	(0.006)	(0.008)	(0.011)

Panel B: Trading volume and return: lagged relations

Dependent variable= Return						
	OLS	**Q05**	**Q25**	**Q50**	**Q75**	**Q95**
Lag volume	-0.001**	-0.006***	-0.005***	-0.001*	0.001	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Constant	0.010**	-0.065***	-0.001	0.009*	0.033***	0.073***
	(0.004)	(0.013)	(0.008)	(0.005)	(0.009)	(0.016)

Note: OLS and QR regression results are from Equation (4.6) and examine the relation between trading volume and stock returns. **Standard errors** are displayed in parentheses below the **coefficients**. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

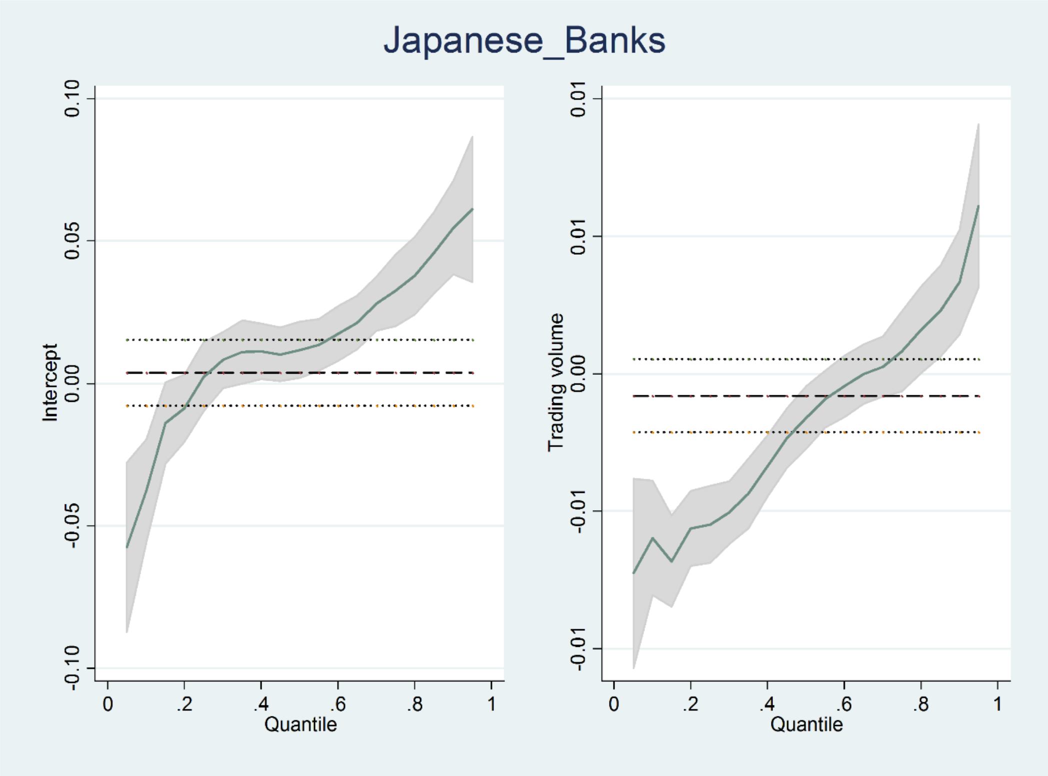
It is noteworthy that two recent articles also investigate the relation between returns and volume using the quantile regression method. Chuang et al. (2009) uses the quantile regressions to show that for the NYSE, S&P500 and FTSE100 indices past trading volume has a positive (negative) impact on price-changes from the top (bottom) of the return distribution and using the same methodology, Gebka and Wohar (2013), find a very similar picture for six emerging Asian markets. Since these studies focus on market indexes and aggregate trading volume, our analysis of individual stock price-changes can shed light on whether the findings can be generalized.

In Panels A of Tables 4.5 (above) and 4.6 (Appendix), it can be seen that, the trading volume coefficients in Equation (4.6), i.e. b_i are statically significant for both aggregate level as well as for each stock in our sample. In general, trading volume has a negative impact on returns in the very lower quantiles (0.05 and 0.25), while trading volume has a positive impact on returns in the higher quantiles (0.95). In general, these results are in line with Chuang et al. (2009), Gebka and Wohar (2013) and Ciner (2015), suggesting that the conclusion on price-volume dynamics could be universal.

In Panel B of both Tables 4.5 (above) and 4.6 (Appendix), we then report the quantile regression results for lagged trading volume. The results show a significant impact of the trading volume on subsequent price-changes. The results from quantile regression show that returns in the lower quantiles always have a negative relation with the lagged volume; on the other hand, returns in the upper quintiles have a positive relation with the lagged volume. These findings, consistent with analysis in Blume et al. (1994), suggests that volume contains information useful for forecasting price variability. The results is also consistent with the prediction of the sequential information model (Copeland 1976; Jennings et al. 1981), where new information disseminates sequentially into the market.

The patterns of b_i in both the panels in Figure 4.5 confirm the non-linear relationship between price-changes and trading volume. Figure 4.5 clearly shows that the regression coefficient (of the volume variable) is an upward sloping function at the quantiles of the stock returns considered. The relation between stock return and volume moves from negative to positive as the quantile increases. At the lower quantiles stock returns are negatively related to volume and at the higher quantiles stock returns are positively related to volume. It is also interesting to note that at the median price changes are correlated with volume but corresponding mean price changes are insignificant.

Figure 4:5: QR and OLS estimates of the effects of trading volume on proce changes
Panel A: Price change and trading volume



Note: The solid line gives the coefficients of trading volume estimates from the quantile regression, with the shaded grey area depicting a 95% confidence interval. The dashed line gives the OLS estimate of mean effect, with two dotted lines again representing a 95% confidence interval for this coefficient.

Panel B: Price changes and lagged trading volume

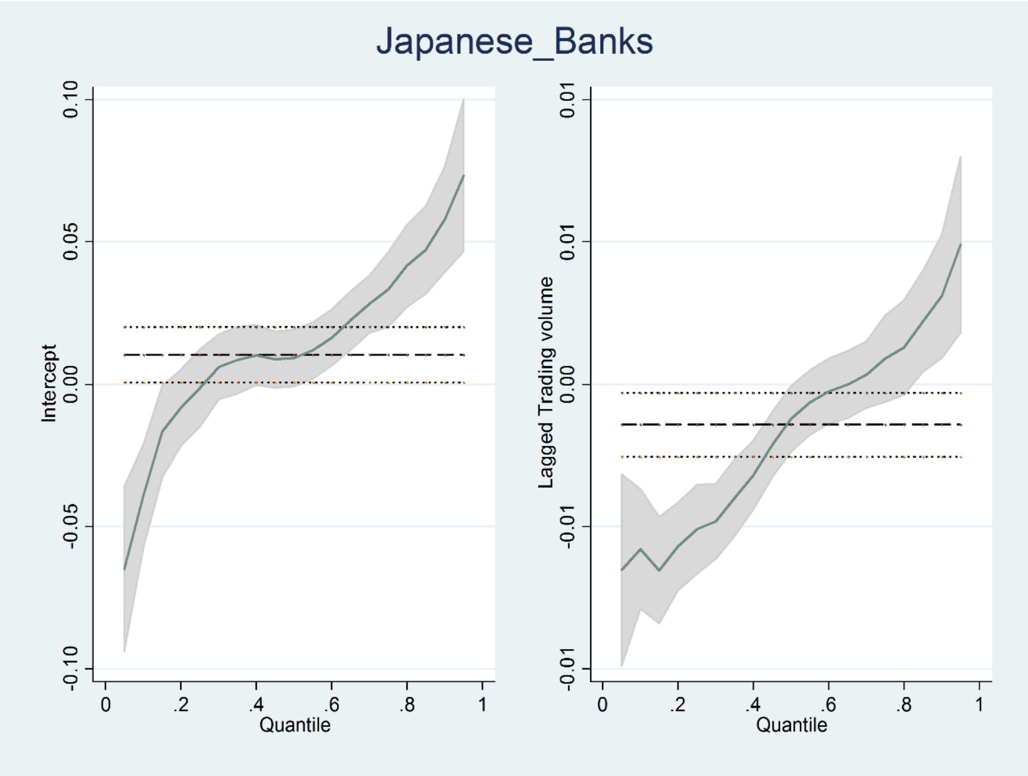
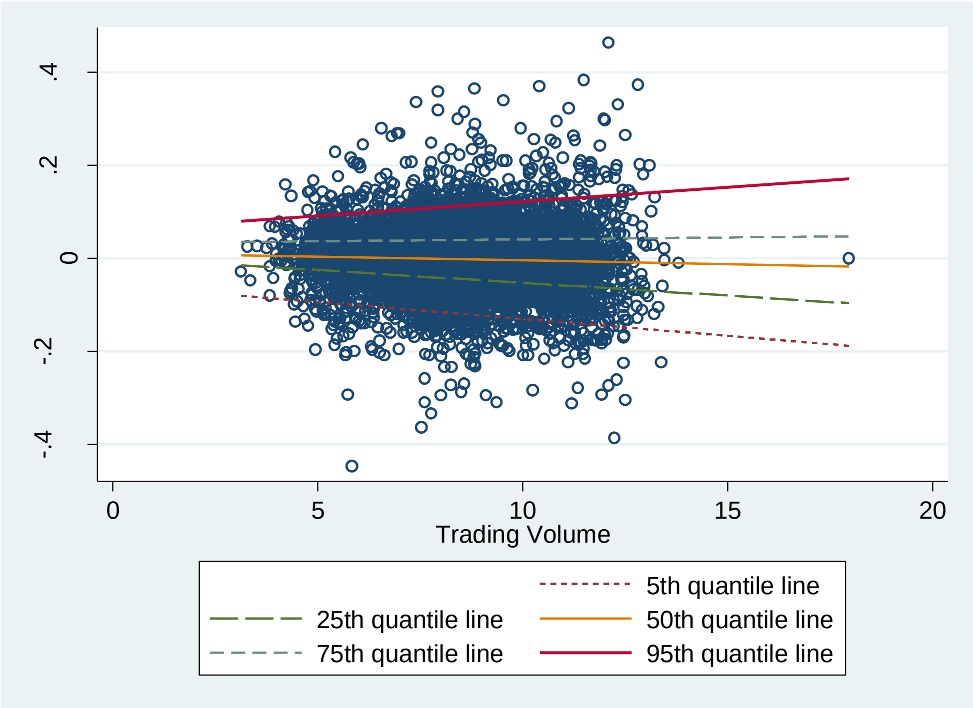
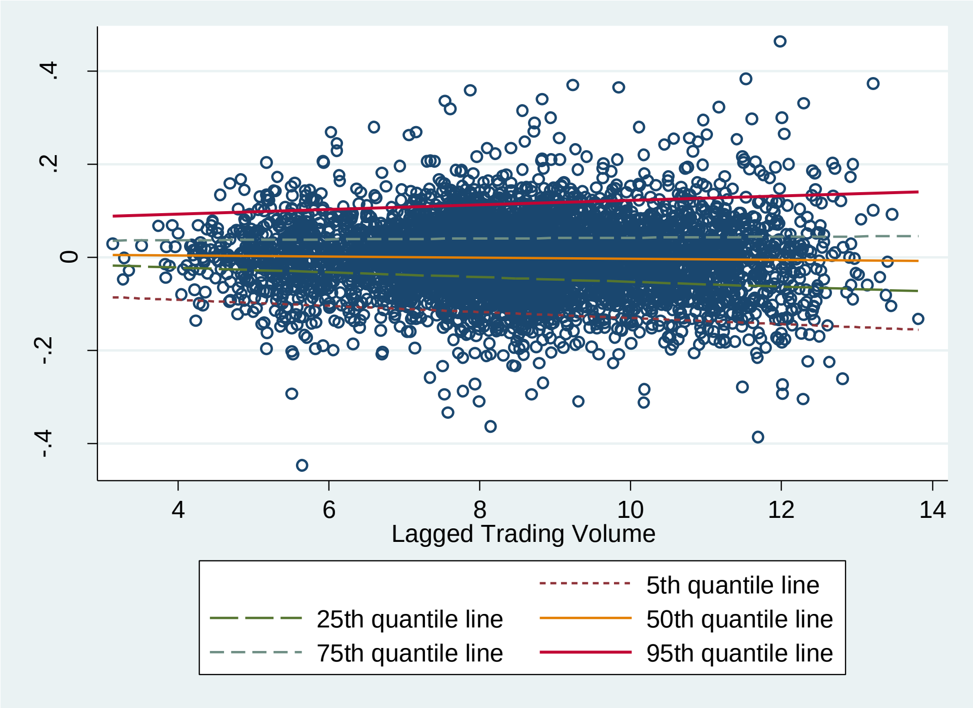


Figure 4.6 presents the regression lines fitted by QR for quantiles of 0.05, 0.25, 0.50, 0.75 and 0.95. In particular, the regression line shows the value of the changes in betas on the y-axis with the trading volume on the x-axis. Interestingly, as shown in Figure 4.6, the price-volume relationship generated by the QR model exhibits a diverging 'cone' or comet shape: positive/negative price-volume relationship for the higher/lower trading volume quantiles.

Figure 4:6: Scatter plot of changes in price and trading volume for individual companies
Panel A: Price changes and trading volume



Panel B: Price changes and lagged trading volume



To summarize, we find from this subsections that there is a non-linear relations between price-changes and volume. As mentioned above, in recent article, Chuang et al. (2009) and Gebka and Wohar (2013) also investigate the dynamic linkages between price-changes and the trading volume in financial markets by relying on stock index data. The results from our paper are almost similar to their findings and thus a price-volume relation in quantiles looks likely to be a universal phenomenon in financial markets. Our empirical results are entirely consistent with the equilibrium model by Llorente et al. (2002), who show that private information and non-informational trading motivates the price-volume relationship.

4.6 Conclusion

In this Chapter, we examine the linkages between trading volume and changes in betas (and changes in prices) for the Japanese banks. We employ empirical techniques which allow volume and changes in betas (and changes in price) to be modelled at a high frequency, a practice not so commonly encountered in the extant literature. Through a decomposition of the standard CAPM beta into two components (diffusion beta and jump beta) we show that trading volume has a statistically significant impact on changes in betas. We find that the trading volume is positively (negatively) related to Δdiffusion beta and Δjump beta at lower quantiles (higher quantiles). The same findings also hold for the relation between trading volume and changes in standard beta. Thus, the Δbeta-volume relationship for Japanese banking stocks is asymmetric across quantiles - the relationships at tail quantiles is quite different from those at high quantiles and at the mean. The findings further show that there is statistically significant relationship between lagged volume and changes in betas. The results are in line with the model of Carpenter and Upton (1981) which states that beta uncertainty can arise from estimation error resulting from 'the inappropriate use of chronological time as an index in the return computation'. They used volume as the instrumental variable to proxy the evolution of the price generation process or to index the operational time.

The study also investigates the quantile relationships between price changes and volume. We find that there a non-linear relation between price changes and volume. Trading volume has significantly negative effects on price-changes at low quantile levels, while there are significantly positive effects at high quantile levels. We also confirm the same findings that trading volume affects subsequent price-changes across the quantiles. The results of the non-linear price-volume relationships in quantiles are in line with the model of Llorente et al. (2002), which highlights the importance of informed trading and non-informed trading in understanding the dynamic price-volume relation.

Overall, the results of the latter study support the argument raised by Gallant et al. (1992), that more can be learned about price-changes by studying the effects of trading volume on price-changes than by just focusing on price-changes alone. In a similar tone, we can also say that more can be learned about time-varying beta by studying the effect of trading volume on beta-changes than just focusing on time-varying beta.

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Chapter 5

Conclusion

Empirical asset pricing literature have been widely documented that stock returns exhibit both stochastic volatility and jumps. Significant jumps have been found in stock prices and equity market indexes, suggesting that jump risk is part of systematic risks. Since jump risk is priced, adding jump risk into the traditional finance models has significant empirical and theoretical meanings. This thesis aims to provide an empirical framework to tie jumps into a fundamental economic model of valuation—the jump-diffusion two-beta asset pricing model. Importantly, this thesis addresses the following questions: To what extent volatility and jump risks factor are priced in the financial market? In particular, what is the market price of the jump risk? Is the jump risk priced differently from the diffusive risk? Answers to these questions have a direct impact on investors' decision-making, and could also shed some light on how investors react to various types of uncertainty. In this these, we address these issues by focusing on testing and exploring the usage of the jump-diffusion two-beta asset pricing model.

This dissertation, investigates the systematic risk exposures of financial firms by modifying the traditional capital asset pricing model (CAPM) framework. Empirical evidence suggests that the traditional CAPM beta has weak explanatory power for the cross sectional pricing behaviour of expected stock returns. One of the reasons that may account for the weak findings is that the CAPM assumes stock returns are generated by a continuous process whilst, in fact, the empirical observation of the stock returns generally also exhibit large discontinuous returns, although at a much lower frequency. Under such circumstances, the CAPM beta may only be a gross measure of systematic risk in what is in effect a mixture of distinct diffusion and jump systematic risks.

In this light, Todorov and Bolleslev's (2010) suggest a two-beta jump-diffusion asset pricing model as an alternative to the traditional single factor CAPM. A stock's diffusion beta captures the stock's sensitivity to diffusive movement and its jump beta captures its sensitivity to jump market movement. In Chapter 2, we seek to understand how an individual firm's equity prices respond to continuous and discrete market moves and how these corresponding distinct systematic risks or betas, are priced. In particular, we investigate the systematic diffusive and jump risks exposures of Japanese banks for the 2000-2012 period. We decompose the time varying betas for stocks into beta for diffusive systematic risk and beta for jump systematic risk. Empirically, we find that the magnitudes of the estimated jump betas generally exceed corresponding magnitudes of the diffusion betas. We then empirically investigate whether the diffusive and jump risks are separately priced under both conditional and unconditional market states. Our empirical findings suggest that jump risks are priced separately from the corresponding diffusive risks. Assuming that investors tend to behave differently under up and down market conditions, we also test whether the risk premiums for diffusion and jump risk are asymmetric under different market conditions. In a separate investigation of upside and downside markets, exposure to both diffusive risk and jump risk are significantly priced. In an upside markets, exposure to diffusive risk and jump risk is rewarded with larger returns whereas these exposures are penalized with greater losses in downside market.

In Chapter 3, using high frequency financial data and associated risk decompositions, we employ quantile regression techniques to explore some stylised fact and relationship(s) between standard betas, diffusion betas and jump betas of individual stocks and portfolios in the Japanese market. We investigate whether the beta in the traditional CAPM is a weighted average of the jump beta and diffusion beta in the jump-diffusion model and how the different betas behave relative to each other. Our empirical findings indicate that the monthly averaged jump betas are more dispersed than the monthly averaged diffusion and standard betas. We also find that standard beta is influenced more by the diffusion beta than the jump beta, although the actual magnitude of the weights differ significantly across the quantiles. Hence, we demonstrate that the relationship(s) between the three betas are non-linear. The non-linear relationship holds for both individual stocks and even of portfolios. Empirical studies have shown that betas vary systematically for large and small firms. Even though betas for large firms are larger than those of small firms, for large equity portfolios, the jump-diffusion beta ratios are lower than the jump-diffusion beta ratios of the small equity portfolios. Finally, we find that the standard CAPM beta acts as a 'summary proxy' for the systematic risk of a mixed-process, i.e. a weighted average of the diffusion component and the jump component; at least at the median quantile.

In chapter 4 of this dissertation, we examine whether changes time-varying betas can be explained by trading volume. The observed time varying betas, prompt an investigation of how firms' beta respond to trading activity. It is widely agreed that in financial markets, trading activity induces price changes and trades directly contribute to price discovery. We find that there is a statistically significant relation between trading volume and changes in betas. Despite the assumption of homogeneous relationships between volume and changes in standard, diffusion and jump betas in the conditional OLS regression analysis, there is strong evidence of a heterogeneous beta-volume relation from the quantile regression. We find a positive relationship between trading volume and changes in diffusion betas at lower quantiles, while a negative beta-volume relationship occurs at higher quantiles. The same findings also hold for the relationship between trading volume and changes in jump beta. We also document the relationship between volume and changes in standard betas from lower quantiles to upper quantiles. The beta-volume relationship implies that the relationship is fundamentally heterogeneous for changes in standard beta, diffusion beta and jump beta. Since the CAPM predicts that changes in beta should be closely associated with price changes (returns) we further investigate the nature of the volume-return relationship. We show a positive volume-return relation in high quantiles, while a negative volume-beta relationship prevails in low quantiles.

Several important contributions emerge from this dissertation. First, the dissertation contributes to the world of asset pricing, when the stylized facts of both diffusion and jump portions of returns have been taken into account, two betas makes more sense than one beta. Using a continuous time finance model where stock prices follow a jump-diffusion process, we investigate a simple but intuitive two-beta model that relates a stock returns to two types of systematic risk exposure as measured by two types of betas: the diffusion beta and the jump beta. A stock's diffusion beta captures the stock's sensitivity to diffusive market movement and its jump beta captures its sensitivity to jump market movement. The estimated jump betas are consistently larger than the diffusion betas in our empirical results, suggesting that, for the Japanese banks stocks analysed here, larger (jump) market moves tend to be associated with proportionally larger systematic risk than smaller more common (diffusion) market moves. Second, this dissertation contributes to the existing literature regarding the role of beta in explaining security returns by applying the return decomposition framework of Todorov and Bollerslev (2010) to disentangle and estimate the time varying systematic risk exposure to diffusion and jump market movements, and the Pettengill et al. (1995) methodology, to examine the conditional relationship between beta and returns. Our results show that market risks with differing degree of jumpiness, as determined by our high-frequency-based-estimator of the diffusion and jump beta, are separately priced and that these cross-sectional differences in the returns cannot be explained by common firm characteristics. This implies that investors in the Japanese market respond differently to diffusion risk and jump risk in the periods of up and down markets. Third, empirical findings from this study show that the systematic risk of an asset is the weighted average of both jump diffusion betas. Fourth, jump beta and diffusion beta are time-varying. While the diffusion beta measures the security's relative risk to the market during normal times, the jump beta measures its relative risk to the market during extraordinary times. This fact should be of interest to portfolio managers and sophisticated investors. Finally, empirical findings from this dissertation lends more support to the role of trading volume in financial markets and also suggests that more can be learned about time-varying beta by studying the effect of trading volume on beta-changes than by just focusing on time-varying beta.

To conclude, this dissertation provides a deeper understanding of how investors behave when faced with diffusive risks as opposed to jump risks including the differing risk premiums demanded for holding stocks with differing sensitivities to continuous and discontinuous market movements. In particular, our results suggest that portfolios designed to hedge large discontinuous market movements might have to be constructed differently from portfolios intended to hedge the more common continuous day-to-day market movements. Thus, disentangling and pricing the two types of systematic risks separately is clearly important for the investment and risk management decisions of portfolio investors and companies.

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Appendix

Appendix A: Chapter 2

Table A1- No of Jump days for the Japanese stock index

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
	20010312	20020111	20030110	20040105	20050105	20060105	20070201	20080123	20090119	20100217	20110104	20120105
	20010507	20020225	20030206	20040109	20050114	20060210	20070402	20080310	20090312	20100219	20110107	20120206
	20010521	20020226	20030207	20040113	20050128	20060323	20070419	20080318	20090323	20100224	20110117	20120208
	20010627	20020304	20030217	20040225	20050214	20060324	20070501	20080407	20090408	20100311	20110210	20120424
	20010709	20020320	20030219	20040303	20050217	20060421	20070523	20080423	20090428	20100324	20110215	20120502
	20010723	20020422	20030305	20040312	20050222	20060502	20070615	20080509	20090525	20100416	20110216	20120510
	20010830	20020423	20030317	20040316	20050304	20060524	20070627	20080520	20090601	20100428	20110318	20120523
	20010917	20020510	20030324	20040318	20050310	20060622	20071003	20080602	20090610	20100507	20110412	20120614
	20010927	20020513	20030327	20040329	20050318	20060728	20071029	20080610	20090624	20100527	20110413	20120626
	20011115	20020523	20030403	20040419	20050404	20060811	20071112	20080611	20090626	20100629	20110502	20120629
	20011119	20020529	20030515	20040622	20050408	20060816		20080701	20090708	20100720	20110614	20120706
	20011130	20020612	20030523	20040625	20050419	20060821		20080707	20090716	20100728	20110705	20120720
	20011210	20020708	20030605	20040705	20050420	20060822		20080708	20090723	20100803	20110707	20120828
	20011220	20020808	20031104	20040713	20050422	20060829		20080715	20090724	20100804	20110715	20120920
		20020815		20040714	20050428	20060908		20080717	20090812	20100810	20110720	20121004
		20020819		20040716	20050523	20060913		20080724	20090818	20100827	20110729	20121026
		20020820		20040720	20050527	20060914		20080729	20090908	20100830	20111012	20121029
		20020924		20040806	20050607	20060929			20091001	20100901	20111027	20121108
		20021007		20040813	20050711	20061129			20091110	20100902	20111116	20121115
		20021028		20040908	20050713	20061211			20091117	20100908	20111129	20121205
		20021029		20040915	20050715				20091118	20100916	20111201	20121217
		20021209		20040929	20050801				20091126	20100917	20111219	
		20021212		20041004	20050802				20091203	20100929	20111230	
		20021216		20041008	20050805				20091207	20100930		
		20021217		20041013	20050822				20091211	20101001		
		20021230		20041014	20050901					20101005		
				20041021	20050902					20101014		
				20041104	20050908					20101118		
				20041111	20050926					20101214		

	20041115	20051031	20101217
	20041119	20051102	
	20041129	20051118	
	20041130	20051227	
	20041201		
	20041206		
	20041209		
	20041216		
	20041228		
	20041229		

Appendix B: Chapter 4

Table 4.3: Changes in betas and trading volume for individual banks
Panel A: Changes in diffusion beta and trading volume

	OLS		Q05		Q25		Q50		Q75		Q95	
	Volume		Volume		Volume		Volume		Volume		Volume	
Aichi Bank	0.944***	(0.245)	1.601*	(0.837)	1.094***	(0.277)	0.762***	(0.188)	0.647***	(0.232)	0.156	(0.954)
Akita Bank	0.251	(0.242)	1.601**	(0.744)	0.894***	(0.227)	0.329	(0.250)	-0.135	(0.306)	-1.489	(0.914)
Aomori Bank	0.071	(0.391)	-0.00283	(0.882)	0.154	(0.440)	0.255	(0.243)	0.034	(0.793)	-1.756**	(0.869)
Aozora Bank	0.267	(0.320)	1.023	(0.923)	0.561*	(0.307)	0.041	(0.286)	-0.001	(0.266)	-0.560	(0.910)
Awa Bank	0.949***	(0.278)	2.647***	(0.651)	0.806***	(0.205)	0.356**	(0.165)	0.122	(0.244)	1.662	(1.495)
Bank Of Iwate	0.618***	(0.228)	2.078***	(0.565)	0.960***	(0.229)	0.554***	(0.138)	0.411	(0.296)	-1.612*	(0.856)
Bank Of Kyoto	0.450***	(0.141)	1.555***	(0.349)	0.636***	(0.186)	0.196	(0.136)	0.008	(0.147)	-0.173	(0.331)
Bank Of Nagoya	0.234	(0.153)	0.740	(0.660)	0.554***	(0.208)	0.158	(0.098)	0.072	(0.282)	-0.328	(0.982)
Bank Of Okinawa	0.649***	(0.204)	2.041***	(0.430)	0.882***	(0.208)	0.329	(0.198)	0.293	(0.305)	0.178	(0.567)
Bank Of The Ryukyus	0.404***	(0.107)	1.118***	(0.209)	0.402***	(0.105)	0.216**	(0.098)	0.154	(0.097)	-0.344	(0.524)
Bank Of Yokohama	-0.148	(0.121)	-0.134	(0.323)	0.051	(0.078)	-0.032	(0.089)	-0.052	(0.151)	-0.676	(0.716)
Chiba Bank	0.333*	(0.172)	1.369***	(0.397)	0.320	(0.248)	0.107	(0.099)	0.117	(0.222)	-0.516	(0.489)
Chugoku Bank	0.676***	(0.182)	2.044***	(0.444)	0.621***	(0.194)	0.245**	(0.116)	0.126	(0.125)	-0.345	(0.730)
Daishi Bank	0.085	(0.279)	0.875	(0.987)	0.534**	(0.263)	0.346***	(0.132)	-0.290	(0.474)	-1.764*	(1.011)
Fukui Bank	0.722**	(0.294)	-0.406	(1.340)	0.920***	(0.277)	0.429	(0.427)	0.601	(0.390)	1.816	(1.630)
Fukuoka Financial Gp.	0.089	(0.235)	0.319	(0.663)	0.062	(0.179)	0.036	(0.204)	-0.116	(0.406)	0.020	(0.584)
Gunma Bank	0.039	(0.136)	1.310***	(0.371)	0.241***	(0.076)	-0.032	(0.108)	-0.434***	(0.164)	-0.418	(0.423)
Hachijuni Bank	0.577***	(0.173)	1.906***	(0.544)	0.586***	(0.203)	0.307***	(0.099)	0.200*	(0.120)	-0.282	(0.792)
Higashi Nippon Bank	0.178	(0.216)	0.300	(0.982)	0.494***	(0.174)	0.068	(0.185)	0.061	(0.198)	-1.116	(0.857)
Higo Bank	0.108	(0.214)	0.210	(0.856)	0.147	(0.171)	-0.066	(0.101)	-0.264	(0.337)	0.985	(1.007)
Hiroshima Bank	0.188	(0.162)	1.261***	(0.293)	0.539***	(0.147)	0.220*	(0.123)	-0.024	(0.133)	-0.903*	(0.467)
Hokkoku Bank	0.169	(0.231)	0.514	(1.243)	0.682***	(0.179)	0.261**	(0.116)	0.109	(0.212)	-1.929	(1.227)

Hokuetsu Bank	0.043	(0.234)	0.177	(0.464)	0.380	(0.320)	0.078	(0.167)	-0.060	(0.156)	-1.766	(1.214)
Hokuhoku Financial Gp.	0.210	(0.262)	0.314	(0.938)	0.581*	(0.332)	0.085	(0.170)	-0.109	(0.289)	-0.964	(1.189)
Hyakugo Bank	0.371*	(0.212)	2.047	(1.571)	0.908***	(0.209)	0.237*	(0.136)	-0.178	(0.263)	-1.356*	(0.814)
Hyakujushi Bank	0.436**	(0.207)	1.581**	(0.692)	0.666**	(0.300)	0.294*	(0.163)	-0.034	(0.232)	-1.814	(1.102)
Iyo Bank	0.406*	(0.231)	1.268	(0.818)	0.808***	(0.187)	0.335***	(0.115)	-0.189	(0.361)	-1.672*	(0.984)
Joyo Bank	-0.012	(0.160)	0.958*	(0.496)	0.316***	(0.086)	0.079	(0.159)	-0.313*	(0.160)	-1.082**	(0.442)
Juroku Bank	0.316	(0.259)	1.844	(1.127)	1.020***	(0.202)	0.240*	(0.143)	0.116	(0.256)	-1.244	(1.014)
Kagoshima Bank	0.623**	(0.245)	1.882***	(0.713)	1.021***	(0.189)	0.448*	(0.233)	-0.103	(0.220)	-1.225*	(0.706)
Keiyo Bank	0.598***	(0.223)	2.445***	(0.479)	0.674**	(0.258)	0.465***	(0.126)	-0.170	(0.259)	-0.836	(1.036)
Miyazaki Bank	0.0416	(0.173)	-0.142	(1.314)	0.347	(0.376)	0.138	(0.166)	0.089	(0.177)	-0.576	(1.292)
Musashino Bank	0.368***	(0.137)	1.184***	(0.228)	0.660***	(0.113)	0.337**	(0.136)	0.038	(0.109)	-1.009*	(0.579)
Nanto Bank	0.701	(1.439)	-1.916	(1.669)	0.758	(1.393)	0.995	(1.314)	1.084	(2.137)	2.963	(3.157)
Nishi-Nippon City Bank	0.094	(0.132)	1.291*	(0.720)	0.250**	(0.111)	0.110	(0.084)	-0.203	(0.155)	-0.214	(0.466)
Ogaki Kyoritsu Bank	0.616***	(0.225)	1.619	(1.096)	0.733***	(0.274)	0.631***	(0.185)	0.302	(0.285)	0.616	(0.795)
Oita Bank	0.389**	(0.169)	0.922	(1.172)	0.602***	(0.196)	0.377**	(0.186)	0.152	(0.150)	0.338	(0.688)
San-In Godo Bank	0.542**	(0.232)	1.187**	(0.488)	0.903***	(0.195)	0.660***	(0.183)	0.009	(0.456)	-2.323*	(1.202)
Seventy-seven Bank	0.008	(0.155)	0.589**	(0.251)	0.193*	(0.103)	0.032	(0.128)	-0.391*	(0.211)	-0.726	(0.526)
Shinsei Bank	-0.309	(0.257)	0.529	(1.520)	-0.709**	(0.278)	-0.333**	(0.141)	-0.205	(0.204)	-0.700	(0.731)
Shizuoka Bank	-0.113	(0.110)	0.061	(0.064)	0.044	(0.106)	0.034	(0.141)	-0.293	(0.202)	-0.514	(0.322)
Sumito Mitsui Financial Gp	-0.024	(0.082)	0.041	(0.532)	0.048	(0.069)	0.017	(0.056)	-0.028	(0.060)	-0.262	(0.493)
Suruga Bank	0.062	(0.219)	1.432***	(0.455)	0.267	(0.211)	0.091	(0.138)	-0.112	(0.202)	-0.629	(0.637)
Tochigi Bank	0.503**	(0.195)	0.780	(1.123)	1.000***	(0.194)	0.277	(0.237)	0.062	(0.205)	-0.296	(1.177)
Toho Bank	0.402	(0.314)	1.404	(0.894)	0.601**	(0.283)	0.138	(0.209)	-0.376	(0.315)	-0.214	(1.454)
Tokoyo Tomin Bank	-0.338	(0.419)	2.273	(1.468)	0.439	(0.726)	0.086	(0.641)	-0.064	(0.565)	-0.853	(0.738)
Yachiyo Bank	0.579	(0.531)	0.680	(0.726)	1.002**	(0.495)	0.299	(0.372)	0.346	(0.823)	0.117	(1.593)
Yamagata Bank	1.169***	(0.343)	1.112	(1.415)	0.829**	(0.414)	0.809***	(0.187)	0.992**	(0.433)	2.469**	(1.076)
Yamaguchi Finl.G.	-0.103	(0.211)	0.286	(0.415)	0.208	(0.155)	0.030	(0.173)	-0.406*	(0.211)	-0.863*	(0.467)

Note: OLS regression results from Equation (4.4) and examine the contemporaneous relation between trading volume and the changes in betas for each bank in our sample. Quantile regression estimates are from Equation (4.5) and test the contemporaneous relation between the variables at specific quantiles for each bank in our sample. **Standard errors** are displayed in parentheses below the **coefficients**. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Panel B: Changes in jump beta and trading volume

	OLS		Q05		Q25		Q50		Q75		Q95	
	Volume		**Volume**		**Volume**		**Volume**		**Volume**		**Volume**	
Aichi Bank	0.172	(0.278)	1.302***	(0.322)	0.369***	(0.102)	0.214	(0.143)	-0.160	(0.286)	-1.490***	(0.473)
Akita Bank	0.551	(0.340)	0.746	(1.199)	0.287	(0.290)	0.028	(0.190)	-0.272	(0.257)	1.934	(1.903)
Aomori Bank	-0.578	(0.367)	-1.410*	(0.819)	0.104	(0.256)	-0.054	(0.109)	-0.166	(0.181)	-1.338	(0.996)
Aozora Bank	0.072	(0.172)	1.088	(0.955)	0.069	(0.113)	0.066	(0.170)	0.142	(0.333)	-0.117	(0.954)
Awa Bank	0.482	(0.352)	1.065	(1.390)	0.344**	(0.158)	0.144	(0.135)	-0.356*	(0.187)	0.211	(0.932)
Bank Of Iwate	-0.690*	(0.377)	-0.137	(1.275)	0.045	(0.129)	-0.107	(0.188)	-0.734***	(0.217)	-2.076***	(0.634)
Bank Of Kyoto	0.533	(0.689)	0.874	(3.655)	0.104	(0.169)	-0.137	(0.134)	-0.044	(0.270)	-1.251**	(0.503)
Bank Of Nagoya	-0.179	(0.198)	-0.062	(0.579)	0.155	(0.102)	0.065	(0.128)	0.035	(0.268)	-0.537	(0.866)
Bank Of Okinawa	0.016	(0.211)	0.791	(0.602)	0.214	(0.310)	0.016	(0.128)	-0.060	(0.149)	-0.694	(1.111)
Bank Of The Ryukyus	0.436**	(0.170)	0.932***	(0.337)	0.530***	(0.169)	0.236*	(0.130)	0.030	(0.268)	-0.194	(0.448)
Bank Of Yokohama	-0.073	(0.140)	0.145**	(0.070)	0.157	(0.122)	0.088	(0.106)	-0.251	(0.265)	-1.005**	(0.446)
Chiba Bank	0.377**	(0.177)	1.745***	(0.538)	0.240	(0.315)	0.165**	(0.067)	0.244	(0.149)	0.021	(0.241)
Chugoku Bank	0.267*	(0.144)	1.068***	(0.237)	0.282*	(0.144)	0.118	(0.090)	-0.057	(0.107)	-0.651	(0.725)
Daishi Bank	0.895	(0.817)	0.841	(5.046)	0.466**	(0.223)	0.066	(0.123)	0.082	(0.235)	-0.172	(0.668)
Fukui Bank	-0.110	(0.268)	0.575	(0.723)	0.373*	(0.208)	0.096	(0.224)	-0.607**	(0.272)	-1.535***	(0.506)
Fukuoka Financial Gp.	0.022	(0.162)	-0.024	(0.161)	0.033	(0.208)	-0.033	(0.181)	0.278	(0.331)	0.763	(0.677)
Gunma Bank	0.217	(0.217)	0.346	(0.963)	0.093	(0.102)	0.051	(0.080)	0.033	(0.167)	-0.347**	(0.138)
Hachijuni Bank	0.159	(0.242)	0.433	(0.800)	0.219**	(0.100)	0.056	(0.091)	-0.141	(0.166)	-0.686	(0.432)
Higashi Nippon Bank	0.665*	(0.387)	1.080	(1.795)	0.610**	(0.282)	0.385**	(0.161)	0.166	(0.236)	-0.272	(2.423)
Higo Bank	0.568**	(0.272)	1.495*	(0.807)	0.372	(0.243)	0.203**	(0.080)	0.285	(0.201)	-0.308	(0.690)
Hiroshima Bank	-0.029	(0.090)	-0.001	(0.249)	0.015	(0.081)	0.007	(0.110)	-0.128	(0.114)	0.325	(0.456)
Hokkoku Bank	0.610	(0.644)	1.340	(2.418)	0.016	(0.255)	-0.008	(0.234)	0.097	(0.350)	-0.241	(0.444)
Hokuetsu Bank	-0.158	(0.158)	-0.705	(0.648)	-0.110	(0.203)	-0.101	(0.116)	-0.126	(0.187)	1.227	(0.840)
Hokuhoku Financial Gp.	-0.621	(0.599)	-0.090	(3.663)	-0.016	(0.120)	-0.039	(0.185)	0.157	(0.244)	-0.589	(1.116)
Hyakugo Bank	-0.132	(0.152)	0.165*	(0.097)	0.222**	(0.090)	0.100	(0.097)	-0.292	(0.192)	-1.123	(1.056)
Hyakujushi Bank	-0.066	(0.217)	0.880***	(0.258)	0.295**	(0.144)	0.086	(0.100)	-0.098	(0.186)	-1.126	(0.860)

Iyo Bank	0.383	(0.271)	1.149	(1.286)	0.411**	(0.202)	0.114	(0.129)	-0.069	(0.165)	-0.700	(0.429)
Joyo Bank	-0.297	(0.235)	0.187	(0.128)	0.096	(0.106)	0.110	(0.131)	-0.233	(0.270)	-1.210	(0.977)
Juroku Bank	0.276	(0.182)	1.431***	(0.525)	0.313**	(0.139)	0.146	(0.144)	0.008	(0.204)	-0.452	(0.404)
Kagoshima Bank	0.169	(0.267)	0.773*	(0.439)	0.424*	(0.230)	0.120	(0.166)	-0.061	(0.207)	-3.571*	(2.136)
Keiyo Bank	-0.684	(1.074)	1.041	(0.642)	0.527***	(0.180)	0.134	(0.109)	-0.102	(0.107)	-0.200	(6.859)
Miyazaki Bank	-0.026	(0.311)	0.227	(2.880)	0.002	(0.182)	0.360	(0.257)	-0.013	(0.223)	0.075	(0.933)
Musashino Bank	-0.410	(0.269)	0.168	(0.667)	0.137	(0.098)	-0.005	(0.187)	-0.557*	(0.298)	-0.886	(1.375)
Nanto Bank	0.357	(0.438)	1.669	(1.733)	0.701	(0.487)	0.099	(0.160)	-0.202	(0.375)	-0.131	(1.587)
Nishi-Nippon City Bank	0.065	(0.203)	1.185***	(0.387)	0.169**	(0.080)	0.093	(0.104)	-0.046	(0.102)	-0.887	(0.782)
Ogaki Kyoritsu Bank	-0.039	(0.165)	0.311	(0.298)	0.101	(0.107)	0.116	(0.122)	-0.097	(0.199)	-1.153*	(0.617)
Oita Bank	0.128	(0.254)	0.826	(0.748)	0.175	(0.131)	0.012	(0.106)	0.048	(0.383)	-0.486	(1.496)
San-In Godo Bank	-0.121	(0.223)	0.309	(0.445)	0.083	(0.085)	0.049	(0.114)	-0.354	(0.315)	-0.853	(0.633)
Seventy-seven Bank	0.085	(0.202)	0.398	(0.808)	0.164**	(0.079)	0.054	(0.106)	-0.143	(0.163)	-0.592**	(0.249)
Shinsei Bank	-0.074	(0.102)	-0.131	(0.164)	-0.247**	(0.116)	-0.163**	(0.080)	-0.002	(0.222)	1.031*	(0.569)
Shizuoka Bank	0.265	(0.189)	0.962	(0.623)	0.120	(0.159)	-0.037	(0.175)	-0.024	(0.168)	0.174	(0.215)
Sumito Mitsui Financial Gp	-0.086	(0.116)	-0.086	(0.142)	-0.030	(0.057)	-0.045	(0.115)	-0.051	(0.159)	-0.467	(0.415)
Suruga Bank	0.644	(1.297)	-0.605	(6.160)	-0.074	(0.164)	-0.093	(0.120)	-0.195	(0.222)	-0.541**	(0.258)
Tochigi Bank	0.311	(0.305)	1.109**	(0.504)	0.203*	(0.118)	0.142	(0.114)	0.093	(0.207)	-0.444	(2.063)
Toho Bank	-0.240	(0.245)	0.818	(1.137)	0.000	(0.192)	-0.175	(0.228)	-0.572*	(0.308)	-0.628	(0.468)
Tokoyo Tomin Bank	0.184	(0.112)	1.991	(2.927)	0.066	(0.389)	0.245	(0.236)	0.032	(0.275)	-0.593	(0.900)
Yachiyo Bank	-0.435	(0.588)	-0.192	(2.815)	-0.387	(0.762)	-0.221	(0.669)	0.394	(0.923)	-0.571	(0.984)
Yamagata Bank	0.269	(0.290)	0.684	(0.491)	0.292	(0.223)	-0.063	(0.170)	-0.162	(0.411)	0.390	(2.790)
Yamaguchi Finl.G.	-0.101	(0.202)	0.381***	(0.117)	0.136	(0.207)	-0.030	(0.164)	-0.122	(0.203)	0.402	(0.772)

Panel C: Changes in standard beta and trading volume

	OLS		Q05		Q25		Q50		Q75		Q95	
	Volume		**Volume**		**Volume**		**Volume**		**Volume**		**Volume**	
Aichi Bank	0.029	(0.150)	0.929***	(0.293)	0.290**	(0.136)	0.027	(0.092)	-0.290	(0.211)	-1.239*	(0.650)
Akita Bank	-0.279	(0.203)	0.264	(0.204)	0.150*	(0.083)	-0.022	(0.107)	-0.309	(0.213)	-1.403**	(0.595)
Aomori Bank	-0.185	(0.154)	0.047	(0.450)	0.026	(0.097)	-0.050	(0.089)	-0.148	(0.153)	-0.769	(0.970)
Aozora Bank	-0.305*	(0.178)	-0.399	(0.390)	-0.056	(0.213)	-0.189	(0.232)	-0.261	(0.192)	-0.511	(0.944)
Awa Bank	-0.118	(0.173)	0.202	(0.300)	0.068	(0.060)	-0.019	(0.066)	-0.047	(0.134)	-1.366***	(0.500)
Bank Of Iwate	-0.048	(0.209)	0.443	(0.310)	0.126	(0.083)	-0.015	(0.063)	-0.254	(0.205)	-1.417**	(0.705)
Bank Of Kyoto	-0.141	(0.137)	0.143**	(0.061)	0.023	(0.058)	-0.035	(0.046)	-0.120	(0.131)	-0.334	(0.486)
Bank Of Nagoya	-0.144	(0.112)	0.109*	(0.066)	0.131*	(0.076)	-0.025	(0.050)	-0.130	(0.083)	-1.012*	(0.586)
Bank Of Okinawa	-0.029	(0.175)	0.704***	(0.154)	0.227*	(0.119)	0.051	(0.103)	-0.006	(0.197)	-1.321***	(0.267)
Bank Of The Ryukyus	-0.124	(0.117)	0.191	(0.185)	0.194***	(0.043)	0.011	(0.055)	-0.182**	(0.090)	-0.738***	(0.277)
Bank Of Yokohama	-0.060	(0.066)	0.045	(0.057)	0.044	(0.074)	-0.042	(0.082)	-0.054	(0.074)	-0.782*	(0.444)
Chiba Bank	-0.158	(0.189)	0.073	(0.100)	-0.083	(0.109)	-0.002	(0.066)	-0.026	(0.156)	-0.119	(0.723)
Chugoku Bank	-0.224	(0.138)	0.120	(0.105)	0.096*	(0.052)	0.009	(0.053)	-0.203*	(0.121)	-0.636	(0.638)
Daishi Bank	-0.009	(0.075)	0.187***	(0.066)	0.026	(0.069)	-0.008	(0.100)	-0.059	(0.101)	-0.508	(0.478)
Fukui Bank	-0.277	(0.221)	0.240**	(0.116)	0.114*	(0.063)	-0.121	(0.144)	-0.460***	(0.167)	-1.310***	(0.458)
Fukuoka Financial Gp.	0.037	(0.150)	-0.006	(0.202)	0.095	(0.165)	-0.050	(0.156)	-0.187	(0.302)	0.277	(0.588)
Gunma Bank	-0.055	(0.051)	0.035	(0.102)	-0.024	(0.047)	-0.070	(0.062)	-0.057	(0.082)	-0.219	(0.137)
Hachijuni Bank	-0.057	(0.060)	-0.082	(0.095)	-0.046	(0.085)	0.0167	(0.047)	-0.045	(0.063)	-0.448	(0.272)
Higashi Nippon Bank	-0.043	(0.163)	0.812	(0.678)	0.197**	(0.091)	-0.027	(0.127)	-0.292	(0.230)	-0.357	(0.670)
Higo Bank	-0.139	(0.153)	0.152	(0.216)	0.092	(0.133)	-0.004	(0.095)	-0.201	(0.121)	-0.984*	(0.555)
Hiroshima Bank	-0.065	(0.102)	0.174***	(0.045)	0.074	(0.060)	-0.007	(0.062)	-0.029	(0.080)	-0.230	(0.393)
Hokkoku Bank	-0.109	(0.118)	0.142*	(0.085)	0.080	(0.068)	-0.013	(0.073)	-0.327**	(0.141)	-0.298	(0.429)
Hokuetsu Bank	-0.106	(0.102)	-0.237	(0.514)	-0.000	(0.066)	-0.118	(0.114)	0.047	(0.112)	-0.238	(0.460)
Hokuhoku Financial Gp.	-0.060	(0.107)	0.052	(0.096)	0.032	(0.099)	-0.010	(0.153)	-0.040	(0.188)	-0.701	(0.705)
Hyakugo Bank	-0.286	(0.210)	0.158***	(0.051)	0.117	(0.081)	0.059	(0.077)	-0.136	(0.139)	-1.367**	(0.546)
Hyakujushi Bank	-0.143	(0.138)	0.302*	(0.158)	0.063	(0.094)	-0.090	(0.066)	-0.195	(0.122)	-1.010*	(0.564)

Iyo Bank	-0.158**	(0.075)	0.217***	(0.071)	0.059	(0.065)	-0.049	(0.051)	-0.242**	(0.109)	-0.699***	(0.147)
Joyo Bank	-0.049	(0.059)	0.095	(0.104)	-0.034	(0.054)	0.019	(0.059)	-0.014	(0.135)	-0.177	(0.191)
Juroku Bank	0.099	(0.103)	0.317	(0.296)	0.113*	(0.067)	0.111*	(0.061)	-0.079	(0.145)	-0.254	(0.266)
Kagoshima Bank	-0.051	(0.167)	0.243	(0.446)	0.153**	(0.062)	-0.055	(0.070)	-0.128	(0.114)	-0.902	(0.715)
Keiyo Bank	-0.130*	(0.069)	0.190*	(0.096)	-0.003	(0.049)	-0.101	(0.063)	-0.237**	(0.117)	-0.593**	(0.290)
Miyazaki Bank	-0.153	(0.163)	0.059	(0.403)	0.088	(0.127)	-0.080	(0.053)	-0.078	(0.175)	-1.442***	(0.432)
Musashino Bank	-0.237*	(0.125)	0.150***	(0.056)	0.054	(0.048)	-0.046	(0.096)	-0.135	(0.098)	-0.731	(0.470)
Nanto Bank	0.156	(0.261)	2.190	(1.594)	0.425	(0.365)	0.048	(0.109)	-0.043	(0.229)	-1.024	(1.477)
Nishi-Nippon City Bank	-0.007	(0.070)	0.229	(0.178)	0.050	(0.031)	0.067**	(0.032)	0.015	(0.081)	-0.692***	(0.232)
Ogaki Kyoritsu Bank	-0.073	(0.083)	0.311	(0.298)	0.101	(0.107)	0.116	(0.122)	-0.097	(0.199)	-1.153*	(0.617)
Oita Bank	-0.100	(0.137)	0.155	(0.140)	0.105**	(0.052)	-0.064	(0.125)	-0.388	(0.309)	-0.397	(0.525)
San-In Godo Bank	-0.088	(0.087)	0.119*	(0.071)	0.043	(0.079)	-0.008	(0.081)	-0.194*	(0.115)	-0.786**	(0.365)
Seventy-seven Bank	-0.175	(0.145)	0.117*	(0.066)	0.048	(0.058)	-0.031	(0.046)	-0.165	(0.133)	-0.849	(0.560)
Shinsei Bank	-0.200*	(0.113)	-0.183	(0.253)	-0.262***	(0.098)	-0.166*	(0.089)	-0.157	(0.225)	0.940	(0.908)
Shizuoka Bank	-0.000	(0.080)	-0.013	(0.119)	-0.114	(0.083)	-0.057	(0.066)	0.034	(0.141)	0.312	(0.353)
Sumito Mitsui Financial Gp	-0.002	(0.091)	0.012	(0.106)	-0.026	(0.048)	-0.063	(0.039)	-0.095	(0.089)	-0.199	(0.215)
Suruga Bank	-0.128	(0.084)	0.111	(0.081)	0.070	(0.111)	-0.060	(0.059)	-0.103	(0.104)	-0.629*	(0.353)
Tochigi Bank	-0.146	(0.135)	0.635***	(0.193)	0.154***	(0.050)	0.032	(0.119)	-0.140	(0.173)	-2.010***	(0.653)
Toho Bank	-0.165	(0.118)	0.165**	(0.064)	0.111	(0.120)	-0.087	(0.084)	-0.156	(0.203)	-0.617	(0.700)
Tokoyo Tomin Bank	0.103	(0.082)	0.241	(0.241)	0.021	(0.132)	0.074	(0.167)	0.172	(0.186)	-0.094	(0.335)
Yachiyo Bank	-0.026	(0.343)	0.097	(0.608)	-0.195	(0.285)	0.031	(0.330)	0.116	(0.647)	-0.393	(0.684)
Yamagata Bank	0.323	(0.296)	0.966**	(0.445)	0.490**	(0.221)	0.178	(0.160)	-0.225	(0.374)	-2.516***	(0.630)
Yamaguchi Finl.G.	0.124	(0.141)	-0.047	(0.182)	-0.015	(0.154)	0.146	(0.223)	0.217	(0.198)	0.151	(0.337)

Table 4.4: Changes in betas and lagged-trading volume for individual banks

Panel A: Changes in diffusion beta and lagged trading volume

	OLS		Q05		Q25		Q50		Q75		Q95	
	Lagvolume		**Lagvolume**		**Lagvolume**		**Lagvolume**		**Lagvolume**		**Lagvolume**	
Aichi Bank	0.765***	(0.228)	1.059	(1.083)	0.933***	(0.230)	0.377*	(0.216)	0.578**	(0.247)	-0.246	(1.155)
Akita Bank	0.303	(0.321)	1.702**	(0.822)	0.920***	(0.207)	0.395*	(0.219)	-0.209	(0.304)	-2.050***	(0.728)
Aomori Bank	0.417	(0.320)	0.374	(1.009)	0.659*	(0.393)	0.339	(0.252)	0.052	(0.566)	-1.712	(1.616)
Aozora Bank	0.315	(0.363)	0.957	(1.652)	0.364	(0.482)	0.256	(0.310)	0.605**	(0.284)	-0.650	(1.118)
Awa Bank	0.721***	(0.259)	1.996*	(1.011)	0.714***	(0.218)	0.270*	(0.157)	-0.030	(0.267)	0.431	(1.646)
Bank Of Iwate	0.608***	(0.216)	2.265***	(0.343)	0.923***	(0.195)	0.391**	(0.164)	0.311	(0.316)	-1.802**	(0.890)
Bank Of Kyoto	0.520***	(0.126)	1.152***	(0.393)	0.623***	(0.195)	0.288**	(0.137)	0.047	(0.123)	0.383	(0.508)
Bank Of Nagoya	0.289	(0.183)	0.652	(0.888)	0.824***	(0.155)	0.347**	(0.151)	0.100	(0.223)	-0.235	(0.920)
Bank Of Okinawa	0.529***	(0.189)	2.200***	(0.764)	0.636***	(0.189)	0.247*	(0.136)	0.247	(0.233)	0.316	(0.477)
Bank Of The Ryukyus	0.284***	(0.109)	1.226***	(0.247)	0.380***	(0.082)	0.156	(0.096)	0.092	(0.102)	-0.441	(0.356)
Bank Of Yokohama	-0.115	(0.149)	-0.122	(0.460)	0.039	(0.077)	-0.066	(0.076)	-0.247	(0.176)	-1.511*	(0.788)
Chiba Bank	0.269	(0.163)	1.106***	(0.417)	0.327	(0.263)	0.050	(0.096)	-0.084	(0.222)	-0.532	(0.338)
Chugoku Bank	0.590***	(0.185)	2.220***	(0.713)	0.589***	(0.211)	0.269**	(0.135)	0.061	(0.145)	-0.317	(0.691)
Daishi Bank	0.237	(0.272)	0.872	(0.849)	0.606***	(0.221)	0.427***	(0.157)	0.137	(0.482)	-1.291	(0.826)
Fukui Bank	0.538	(0.325)	1.447	(1.004)	0.899***	(0.272)	0.256	(0.296)	0.110	(0.369)	1.521	(1.674)
Fukuoka Financial	-0.256	(0.236)	0.152	(0.415)	-0.083	(0.173)	-0.206	(0.182)	-0.509	(0.390)	-0.457	(0.590)
Gunma Bank	0.087	(0.128)	1.355***	(0.393)	0.235***	(0.081)	0.016	(0.120)	-0.335*	(0.190)	-0.524	(0.467)
Hachijuni Bank	0.526***	(0.196)	2.009***	(0.486)	0.416*	(0.218)	0.210**	(0.099)	0.185	(0.169)	-0.303	(0.890)
Higashi Nippon Bank	0.198	(0.195)	0.205	(1.673)	0.619***	(0.209)	0.180	(0.157)	0.069	(0.192)	-1.167	(0.704)
Higo Bank	0.167	(0.307)	-0.133	(0.887)	0.028	(0.268)	-0.030	(0.166)	0.027	(0.375)	0.473	(0.775)
Hiroshima Bank	-0.001	(0.166)	0.892	(0.579)	0.450***	(0.157)	0.120	(0.104)	-0.081	(0.126)	-0.825**	(0.335)
Hokkoku Bank	0.390	(0.291)	1.610*	(0.849)	0.685***	(0.156)	0.360***	(0.133)	0.200	(0.245)	-0.357	(1.198)
Hokuetsu Bank	0.258	(0.235)	0.189	(0.532)	0.490*	(0.262)	0.118	(0.110)	-0.047	(0.216)	-1.985	(1.500)
Hokuhoku Financial	0.708**	(0.297)	1.890*	(0.960)	0.771***	(0.269)	0.291	(0.195)	0.038	(0.352)	0.403	(1.063)

Hyakugo Bank	0.307	(0.260)	2.498**	(1.212)	0.892***	(0.278)	0.240*	(0.125)	-0.209	(0.240)	-1.294**	(0.601)
Hyakujushi Bank	0.406	(0.285)	1.721*	(0.954)	0.729***	(0.214)	0.390**	(0.155)	-0.201	(0.293)	-2.036*	(1.041)
Iyo Bank	0.358*	(0.207)	1.132**	(0.457)	0.728***	(0.179)	0.315**	(0.121)	-0.161	(0.343)	-1.517*	(0.822)
Joyo Bank	-0.059	(0.175)	1.024**	(0.497)	0.221**	(0.104)	0.052	(0.172)	-0.258	(0.249)	-1.138***	(0.430)
Juroku Bank	0.344	(0.230)	1.797	(1.167)	0.945***	(0.285)	0.299*	(0.169)	0.173	(0.231)	-0.994	(1.244)
Kagoshima Bank	0.467**	(0.213)	1.861*	(1.088)	0.984***	(0.235)	0.374*	(0.213)	-0.172	(0.159)	-1.186	(0.766)
Keiyo Bank	0.582***	(0.202)	2.543***	(0.669)	0.799***	(0.250)	0.373***	(0.134)	-0.078	(0.282)	-0.778	(1.021)
Miyazaki Bank	0.304	(0.242)	0.447	(0.509)	0.495	(0.358)	0.190	(0.154)	0.088	(0.237)	0.270	(1.121)
Musashino Bank	0.316**	(0.123)	1.297***	(0.283)	0.604***	(0.139)	0.267***	(0.101)	0.004	(0.148)	-1.110**	(0.492)
Nanto Bank	-0.177	(0.644)	-2.703	(2.107)	0.447	(0.783)	0.064	(0.675)	-0.508	(0.778)	3.451	(4.462)
Nishi-Nippon City	0.096	(0.121)	1.046	(0.836)	0.236*	(0.128)	0.104	(0.083)	-0.157	(0.149)	-0.326	(0.399)
Ogaki Kyoritsu Bank	0.628***	(0.210)	1.348	(0.887)	0.818***	(0.240)	0.542***	(0.141)	0.285	(0.315)	0.473	(0.635)
Oita Bank	0.451**	(0.183)	1.132	(0.881)	0.706***	(0.266)	0.430**	(0.171)	0.123	(0.219)	0.571	(0.617)
San-In Godo Bank	0.545**	(0.266)	1.725***	(0.561)	1.055***	(0.149)	0.782***	(0.226)	0.009	(0.414)	-3.007***	(1.090)
Seventy-seven Bank	0.027	(0.169)	0.764**	(0.329)	0.339**	(0.133)	0.065	(0.136)	-0.237	(0.233)	-0.370	(0.362)
Shinsei Bank	-0.093	(0.426)	-0.947	(1.594)	-0.461	(0.432)	-0.357	(0.229)	-0.083	(0.262)	0.333	(0.721)
Shizuoka Bank	-0.108	(0.097)	0.051	(0.059)	0.018	(0.096)	-0.069	(0.133)	-0.381**	(0.187)	-0.208	(0.304)
Sumito Mitsui Fin.	-0.034	(0.121)	0.021	(0.474)	-0.043	(0.071)	-0.035	(0.057)	-0.088	(0.124)	0.101	(0.642)
Suruga Bank	0.148	(0.220)	1.429***	(0.425)	0.347	(0.234)	0.049	(0.179)	-0.152	(0.192)	-0.643	(0.724)
Tochigi Bank	0.609***	(0.195)	2.118**	(1.056)	0.907***	(0.171)	0.631***	(0.234)	0.248	(0.197)	0.868	(0.993)
Toho Bank	0.065	(0.289)	-0.164	(1.149)	0.461*	(0.254)	0.030	(0.217)	-0.387	(0.339)	-0.940	(1.062)
Tokoyo Tomin Bank	0.221	(0.156)	1.711**	(0.822)	0.213	(0.466)	0.359	(0.229)	0.121	(0.492)	-1.361	(1.409)
Yachiyo Bank	0.336	(0.293)	0.819	(0.820)	0.406	(0.316)	0.158	(0.192)	-0.201	(0.447)	-1.842	(2.098)
Yamagata Bank	1.080**	(0.415)	2.447**	(1.116)	1.088***	(0.349)	0.619**	(0.283)	0.468	(0.552)	1.632	(1.157)
Yamaguchi Finl.G.	-0.029	(0.181)	0.141	(0.702)	0.135	(0.139)	0.032	(0.137)	-0.387	(0.257)	-0.801	(0.607)

Note: Regression results from Equation (4.4) and examine the lagged relation between trading volume and the changes in betas for each bank in our sample. Quantile regression estimates are from Equation (4.5) and test the lagged relation between the variables at specific quantiles for each bank in our sample. **Standard errors** are displayed in parentheses below the **coefficients**. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Panel B: Changes in jump beta and lagged trading volume

	OLS		Q05		Q25		Q50		Q75		Q95	
	Lagvolume		**Lagvolume**		**Lagvolume**		**Lagvolume**		**Lagvolume**		**Lagvolume**	
Aichi Bank	0.223	(0.264)	1.200**	(0.511)	0.309***	(0.087)	0.298**	(0.149)	-0.162	(0.303)	-1.619***	(0.432)
Akita Bank	1.172**	(0.562)	1.222	(2.048)	0.471	(0.360)	0.453*	(0.265)	0.109	(0.508)	1.861	(1.664)
Aomori Bank	-0.140	(0.326)	0.287	(0.601)	0.116	(0.144)	0.073	(0.137)	-0.083	(0.252)	-1.099	(1.145)
Aozora Bank	-0.203	(0.243)	-1.601	(1.116)	-0.136	(0.185)	0.085	(0.286)	0.116	(0.464)	-0.104	(0.990)
Awa Bank	0.293	(0.300)	0.831	(1.434)	0.314***	(0.109)	0.144	(0.163)	-0.216	(0.236)	-0.582	(0.998)
Bank Of Iwate	-0.383	(0.344)	-0.126	(1.229)	0.183	(0.116)	0.180	(0.162)	-0.465*	(0.270)	-2.063**	(0.874)
Bank Of Kyoto	0.388	(0.604)	0.722	(3.826)	0.268*	(0.150)	-0.001	(0.192)	-0.125	(0.300)	-1.486***	(0.362)
Bank Of Nagoya	-0.124	(0.200)	0.006	(0.602)	0.148*	(0.088)	0.076	(0.121)	0.047	(0.178)	-0.299	(0.866)
Bank Of Okinawa	-0.021	(0.207)	0.669	(0.744)	0.202	(0.336)	0.022	(0.114)	-0.089	(0.131)	-0.602	(0.955)
Bank Of The Ryukyus	0.411**	(0.176)	0.874**	(0.395)	0.517***	(0.190)	0.248*	(0.135)	-0.067	(0.217)	-0.242	(0.400)
Bank Of Yokohama	-0.048	(0.126)	0.139**	(0.068)	0.300***	(0.092)	0.127	(0.123)	-0.263	(0.282)	-1.249***	(0.435)
Chiba Bank	0.435**	(0.183)	1.484***	(0.286)	0.336	(0.434)	0.224**	(0.106)	0.012	(0.227)	-0.290	(0.251)
Chugoku Bank	0.121	(0.201)	0.996**	(0.460)	0.202*	(0.118)	0.076	(0.092)	-0.145	(0.141)	-0.532	(1.023)
Daishi Bank	0.426	(0.268)	0.432	(3.120)	0.435***	(0.138)	0.076	(0.139)	0.075	(0.230)	-0.218	(0.739)
Fukui Bank	-0.159	(0.290)	0.406	(0.700)	0.438	(0.270)	0.213	(0.231)	-0.511**	(0.251)	-1.202	(0.992)
Fukuoka Financial	0.044	(0.119)	-0.149	(0.195)	0.149	(0.314)	0.038	(0.144)	-0.012	(0.283)	0.812	(0.651)
Gunma Bank	0.182	(0.181)	0.296	(1.002)	0.088	(0.103)	0.019	(0.080)	0.023	(0.162)	-0.362	(0.288)
Hachijuni Bank	0.172	(0.209)	0.534	(0.786)	0.171*	(0.100)	0.083	(0.099)	-0.130	(0.191)	-0.548	(0.568)
Higashi Nippon Bank	0.451	(0.391)	1.034	(1.925)	0.480*	(0.288)	0.323***	(0.119)	0.078	(0.344)	-1.015	(1.633)
Higo Bank	0.551***	(0.202)	0.804	(1.233)	0.322*	(0.169)	0.224***	(0.036)	0.246	(0.213)	0.0354	(0.613)
Hiroshima Bank	0.002	(0.111)	0.007	(0.349)	0.065	(0.089)	0.021	(0.100)	-0.130	(0.175)	0.308	(0.513)
Hokkoku Bank	0.487	(0.435)	1.283	(1.894)	0.296	(0.243)	0.236	(0.186)	0.201	(0.173)	-0.115	(0.322)
Hokuetsu Bank	-0.030	(0.184)	-0.159	(0.579)	-0.075	(0.224)	-0.124	(0.082)	0.061	(0.222)	1.068	(0.793)
Hokuhoku Financial	-0.522	(0.401)	-0.147	(3.993)	0.014	(0.132)	0.049	(0.173)	-0.107	(0.262)	-0.947	(0.660)
Hyakugo Bank	-0.144	(0.172)	0.168**	(0.070)	0.234***	(0.075)	0.092	(0.160)	-0.255	(0.284)	-0.431	(0.970)
Hyakujushi Bank	0.016	(0.235)	0.705**	(0.300)	0.261**	(0.131)	0.238*	(0.131)	-0.150	(0.229)	-1.131	(1.284)

Iyo Bank	0.518*	(0.305)	1.211	(1.062)	0.407***	(0.147)	0.094	(0.147)	-0.083	(0.178)	-0.152	(0.470)
Joyo Bank	-0.319	(0.233)	0.309**	(0.126)	0.114	(0.105)	0.078	(0.138)	-0.230	(0.256)	-1.375*	(0.810)
Juroku Bank	0.309*	(0.177)	1.106*	(0.577)	0.321**	(0.148)	0.194	(0.161)	0.014	(0.178)	-0.344	(0.547)
Kagoshima Bank	0.266	(0.260)	0.872*	(0.441)	0.482***	(0.159)	0.192	(0.159)	-0.055	(0.230)	-0.910	(2.213)
Keiyo Bank	-1.247	(1.621)	1.588***	(0.562)	0.470***	(0.148)	0.161	(0.115)	0.001	(0.145)	-0.434	(7.980)
Miyazaki Bank	-0.370	(0.273)	-2.400	(2.064)	0.015	(0.183)	0.206	(0.289)	-0.069	(0.248)	0.0556	(0.917)
Musashino Bank	-0.398	(0.309)	0.125	(0.728)	0.159*	(0.091)	0.006	(0.132)	-0.505	(0.313)	-1.328	(1.081)
Nanto Bank	-0.420	(0.674)	0.678	(1.543)	0.584	(0.439)	0.282	(0.215)	0.131	(0.609)	-2.979	(4.078)
Nishi-Nippon City	-0.007	(0.209)	1.241**	(0.519)	0.221***	(0.081)	0.091	(0.100)	-0.108	(0.173)	-0.928	(0.714)
Ogaki Kyoritsu Bank	-0.104	(0.208)	0.281	(0.374)	0.170	(0.114)	0.175	(0.153)	-0.114	(0.258)	-1.004**	(0.425)
Oita Bank	0.020	(0.249)	0.944**	(0.466)	0.169*	(0.096)	0.023	(0.113)	-0.009	(0.268)	-1.419	(1.436)
San-In Godo Bank	-0.037	(0.202)	0.496	(0.482)	0.160*	(0.086)	0.048	(0.116)	-0.191	(0.249)	-1.321*	(0.735)
Seventy-seven Bank	0.077	(0.209)	0.321	(0.724)	0.087	(0.079)	0.006	(0.113)	-0.159	(0.162)	-0.594***	(0.221)
Shinsei Bank	0.175	(0.206)	-0.098	(0.240)	-0.064	(0.146)	-0.137	(0.145)	0.092	(0.272)	0.819*	(0.447)
Shizuoka Bank	0.191	(0.163)	0.878	(0.652)	0.073	(0.178)	-0.074	(0.185)	-0.085	(0.120)	0.037	(0.204)
Sumito Mitsui Fin.	-0.101	(0.098)	-0.137	(0.161)	-0.050	(0.058)	-0.055	(0.102)	-0.063	(0.149)	-0.403	(0.407)
Suruga Bank	0.041	(0.561)	-0.446	(5.413)	0.043	(0.132)	-0.061	(0.109)	0.011	(0.198)	-0.504*	(0.290)
Tochigi Bank	0.114	(0.252)	0.192	(0.516)	0.213	(0.129)	0.101	(0.132)	0.020	(0.182)	-0.789	(1.694)
Toho Bank	-0.170	(0.248)	0.560	(1.123)	-0.061	(0.161)	-0.184	(0.175)	-0.432	(0.317)	-0.814	(0.678)
Tokoyo Tomin Bank	0.238*	(0.137)	1.673	(2.048)	0.060	(0.492)	0.164	(0.296)	0.421	(0.348)	0.765	(0.799)
Yachiyo Bank	0.501	(0.418)	0.847	(3.587)	0.183	(0.884)	0.605	(0.660)	0.497	(0.627)	0.027	(3.118)
Yamagata Bank	0.328	(0.339)	0.832	(0.794)	0.360*	(0.194)	0.222	(0.216)	0.094	(0.436)	-2.074	(2.578)
Yamaguchi Finl.G.	-0.095	(0.139)	0.322**	(0.131)	0.103	(0.176)	-0.057	(0.196)	-0.060	(0.126)	-0.732	(1.052)

Panel C: Changes in standard beta and lagged trading volume

	OLS		Q05		Q25		Q50		Q75		Q95	
	Lagvolume		**Lagvolume**		**Lagvolume**		**Lagvolume**		**Lagvolume**		**Lagvolume**	
Aichi Bank	0.165	(0.189)	0.794***	(0.244)	0.377***	(0.124)	0.093	(0.140)	-0.313	(0.229)	-1.200	(0.765)
Akita Bank	-0.198	(0.170)	0.179	(0.142)	0.120*	(0.067)	-0.044	(0.101)	-0.288*	(0.164)	-1.096*	(0.649)
Aomori Bank	-0.187	(0.154)	0.138	(0.091)	0.004	(0.095)	-0.085	(0.073)	-0.223*	(0.133)	-1.243	(0.854)
Aozora Bank	-0.207	(0.164)	-0.152	(0.583)	0.038	(0.111)	-0.177	(0.198)	-0.210	(0.217)	-1.422*	(0.736)
Awa Bank	-0.116	(0.203)	0.161	(0.288)	0.087	(0.058)	-0.010	(0.070)	-0.033	(0.192)	-1.271	(0.808)
Bank Of Iwate	-0.022	(0.201)	0.548**	(0.224)	0.171*	(0.088)	0.009	(0.066)	-0.165	(0.245)	-1.481	(1.123)
Bank Of Kyoto	-0.098	(0.094)	0.105*	(0.062)	0.018	(0.055)	-0.033	(0.054)	-0.145*	(0.083)	-0.230	(0.301)
Bank Of Nagoya	-0.137	(0.088)	0.113**	(0.045)	0.073	(0.078)	-0.021	(0.059)	-0.147	(0.118)	-1.222**	(0.523)
Bank Of Okinawa	-0.020	(0.155)	0.754***	(0.216)	0.257**	(0.107)	0.016	(0.072)	-0.015	(0.251)	-1.251***	(0.474)
Bank Of Ryukyus	-0.085	(0.115)	0.148	(0.191)	0.188***	(0.052)	0.008	(0.052)	-0.172*	(0.097)	-0.848***	(0.242)
Bank Of Yokohama	-0.066	(0.061)	0.067	(0.051)	0.058	(0.055)	-0.087	(0.054)	-0.064	(0.089)	-0.890**	(0.373)
Chiba Bank	-0.156	(0.144)	0.071	(0.112)	-0.107	(0.097)	-0.061	(0.076)	-0.090	(0.144)	-0.106	(0.858)
Chugoku Bank	-0.152	(0.121)	0.244***	(0.091)	0.081*	(0.043)	0.006	(0.066)	-0.178	(0.151)	-0.265	(0.614)
Daishi Bank	-0.033	(0.088)	0.213***	(0.074)	0.044	(0.078)	-0.014	(0.087)	-0.130	(0.087)	-0.672	(0.432)
Fukui Bank	0.149	(0.266)	0.263	(0.167)	0.175*	(0.092)	0.089	(0.142)	-0.214	(0.193)	-0.767	(0.653)
Fukuoka Financial	-0.292***	(0.096)	-0.017	(0.242)	-0.167	(0.130)	-0.233**	(0.111)	-0.393**	(0.159)	-0.824	(0.635)
Gunma Bank	-0.045	(0.052)	0.034	(0.086)	-0.033	(0.044)	-0.081	(0.053)	-0.046	(0.084)	-0.084	(0.145)
Hachijuni Bank	-0.026	(0.056)	-0.063	(0.112)	-0.005	(0.066)	0.030	(0.044)	-0.005	(0.053)	-0.078	(0.313)
Higashi Nippon Bank	-0.077	(0.179)	0.135	(0.843)	0.182**	(0.073)	-0.055	(0.129)	-0.348*	(0.196)	-0.054	(0.892)
Higo Bank	-0.145	(0.147)	0.299	(0.279)	0.144	(0.117)	-0.062	(0.095)	-0.090	(0.198)	-0.662	(0.581)
Hiroshima Bank	-0.153	(0.100)	0.150**	(0.075)	0.032	(0.066)	-0.022	(0.064)	-0.093	(0.109)	-0.855**	(0.411)
Hokkoku Bank	-0.008	(0.088)	0.112	(0.072)	0.085	(0.078)	-0.019	(0.067)	-0.180	(0.163)	-0.293	(0.272)
Hokuetsu Bank	-0.140	(0.113)	-0.061	(0.676)	-0.016	(0.065)	-0.154**	(0.077)	-0.055	(0.144)	-0.072	(0.519)
Hokuhoku Financial	-0.191	(0.150)	0.028	(0.102)	0.073	(0.075)	0.070	(0.161)	-0.132	(0.234)	-0.785***	(0.253)
Hyakugo Bank	-0.295	(0.214)	0.189***	(0.057)	0.080	(0.064)	0.047	(0.079)	-0.187	(0.146)	-1.318**	(0.527)
Hyakujushi Bank	-0.140	(0.128)	0.304**	(0.144)	0.048	(0.092)	-0.080	(0.059)	-0.222*	(0.120)	-0.978**	(0.425)

Iyo Bank	-0.123	(0.076)	0.192***	(0.046)	0.063	(0.064)	-0.054	(0.062)	-0.210	(0.130)	-0.664***	(0.186)
Joyo Bank	-0.090	(0.061)	0.077	(0.100)	-0.042	(0.048)	-0.052	(0.064)	-0.233**	(0.117)	-0.302	(0.190)
Juroku Bank	0.036	(0.103)	0.216	(0.325)	0.136**	(0.067)	0.072	(0.060)	-0.177	(0.164)	-0.410	(0.266)
Kagoshima Bank	0.011	(0.169)	0.270	(0.415)	0.219***	(0.083)	-0.002	(0.098)	-0.126	(0.080)	-1.605*	(0.818)
Keiyo Bank	-0.171**	(0.085)	0.160**	(0.072)	-0.003	(0.054)	-0.097*	(0.057)	-0.224	(0.145)	-0.699***	(0.206)
Miyazaki Bank	0.016	(0.164)	0.606	(0.402)	0.118	(0.093)	-0.055	(0.061)	-0.172	(0.230)	-0.652	(0.517)
Musashino Bank	-0.303**	(0.151)	0.164***	(0.061)	0.058	(0.061)	-0.066	(0.096)	-0.249**	(0.096)	-1.320***	(0.316)
Nanto Bank	0.092	(0.264)	1.371	(0.940)	0.239	(0.414)	0.145	(0.142)	0.171	(0.374)	0.311	(1.324)
Nishi-Nippon City	-0.018	(0.069)	0.311	(0.193)	0.035	(0.022)	0.058	(0.036)	-0.023	(0.091)	-0.632**	(0.259)
Ogaki Kyoritsu Bank	-0.079	(0.073)	0.311*	(0.188)	0.035	(0.031)	0.058	(0.040)	-0.023	(0.099)	-0.632**	(0.255)
Oita Bank	-0.111	(0.117)	0.125**	(0.059)	0.091**	(0.044)	-0.035	(0.099)	-0.300	(0.226)	-0.703	(0.441)
San-In Godo Bank	-0.052	(0.095)	0.098	(0.092)	0.051	(0.062)	0.042	(0.075)	-0.066	(0.147)	-0.713*	(0.390)
Seventy-seven Bank	-0.110	(0.114)	0.074	(0.054)	0.075	(0.068)	-0.027	(0.052)	-0.061	(0.135)	-0.690	(0.565)
Shinsei Bank	0.151	(0.184)	-0.097	(0.064)	-0.178**	(0.087)	-0.126	(0.101)	0.061	(0.282)	1.001***	(0.227)
Shizuoka Bank	-0.041	(0.075)	-0.009	(0.099)	-0.117	(0.081)	-0.093	(0.071)	-0.005	(0.132)	0.160	(0.272)
Sumito Mitsui Fin.	0.016	(0.110)	0.064	(0.073)	0.020	(0.072)	-0.027	(0.048)	-0.179	(0.109)	-0.426	(0.374)
Suruga Bank	-0.047	(0.063)	0.178***	(0.059)	0.058	(0.095)	-0.023	(0.041)	-0.107	(0.104)	-0.717*	(0.429)
Tochigi Bank	-0.134	(0.131)	0.634***	(0.179)	0.162***	(0.060)	-0.014	(0.119)	-0.214	(0.228)	-2.046***	(0.426)
Toho Bank	-0.178	(0.125)	0.123	(0.088)	0.089	(0.101)	-0.078	(0.082)	-0.156	(0.227)	-0.548	(0.417)
Tokoyo Tomin Bank	0.064	(0.082)	0.208	(0.182)	0.008	(0.139)	0.053	(0.186)	0.169	(0.249)	-0.169	(0.304)
Yachiyo Bank	0.211	(0.236)	0.848	(0.514)	0.209	(0.198)	0.086	(0.293)	0.343	(0.386)	-0.414	(0.811)
Yamagata Bank	0.218	(0.341)	0.907	(0.663)	0.269	(0.163)	0.213	(0.164)	-0.292	(0.409)	-2.361***	(0.795)
Yamaguchi Finl.G.	-0.021	(0.134)	-0.015	(0.129)	-0.057	(0.094)	-0.077	(0.157)	-0.069	(0.265)	0.159	(0.357)

Table 4.6: Changes in prices and trading volume for individual banks

Panel A: Changes in prices and trading volume for individual banks

	OLS		**Q05**		**Q25**		**Q50**		**Q75**		**Q95**	
	Volume		**Volume**		**Volume**		**Volume**		**Volume**		**Volume**	
Aichi Bank	-0.004	(0.008)	-0.034**	(0.017)	-0.011	(0.010)	-0.018*	(0.010)	0.010	(0.009)	0.034	(0.020)
Akita Bank	-0.009	(0.009)	-0.025	(0.033)	-0.019*	(0.011)	-0.010	(0.009)	-0.002	(0.015)	0.029	(0.024)
Aomori Bank	-0.012	(0.010)	-0.044**	(0.022)	-0.018*	(0.010)	-0.010	(0.008)	0.005	(0.008)	-0.003	(0.012)
Aozora Bank	-0.042	(0.027)	-0.098	(0.167)	-0.057	(0.041)	-0.038	(0.025)	-0.032	(0.034)	0.101	(0.083)
Awa Bank	-0.011	(0.007)	-0.034**	(0.014)	-0.016	(0.010)	-0.001	(0.006)	-0.009	(0.006)	0.016	(0.025)
Bank Of Iwate	-0.010	(0.007)	-0.002	(0.017)	-0.015	(0.014)	-0.011	(0.008)	-0.014*	(0.008)	0.016	(0.027)
Bank Of Kyoto	-0.008	(0.007)	-0.005	(0.013)	-0.007	(0.009)	0.000	(0.009)	-0.003	(0.012)	-0.021	(0.014)
Bank Of Nagoya	-0.011	(0.006)	-0.016	(0.022)	-0.024***	(0.009)	-0.017*	(0.010)	0.000	(0.012)	0.024*	(0.013)
Bank Of Okinawa	-0.003	(0.006)	-0.060***	(0.021)	-0.019**	(0.009)	-0.004	(0.006)	0.022**	(0.010)	0.028	(0.024)
Bank Of The Ryukyus	-0.010	(0.007)	-0.041	(0.014)	-0.025***	(0.005)	-0.013**	(0.005)	0.016*	(0.009)	0.040***	(0.015)
Bank Of Yokohama	-0.009	(0.012)	-0.007	(0.028)	0.000	(0.011)	0.014	(0.014)	-0.005	(0.029)	-0.007	(0.033)
Chiba Bank	-0.013	(0.013)	-0.015	(0.024)	0.006	(0.018)	-0.011	(0.016)	-0.018	(0.017)	0.029	(0.064)
Chugoku Bank	-0.012	(0.0075)	-0.001	(0.012)	-0.011	(0.011)	-0.006	(0.009)	-0.024*	(0.014)	-0.013	(0.019)
Daishi Bank	-0.017**	(0.0072)	-0.008	(0.021)	-0.017**	(0.007)	-0.021	(0.014)	-0.018*	(0.011)	0.000	(0.009)
Fukui Bank	-0.002	(0.012)	-0.013	(0.052)	-0.010	(0.015)	-0.004	(0.014)	-0.004	(0.015)	0.004	(0.015)
Fukuoka Financial Gp.	-0.068*	(0.039)	-0.071	(0.082)	-0.125**	(0.062)	-0.070	(0.050)	-0.044	(0.048)	-0.051	(0.093)
Gunma Bank	-0.004	(0.007)	-0.009	(0.013)	-0.006	(0.007)	-0.002	(0.007)	0.011	(0.012)	0.010	(0.017)
Hachijuni Bank	-0.010	(0.007)	-0.018	(0.018)	-0.010	(0.009)	-0.002	(0.013)	-0.005	(0.012)	-0.038*	(0.021)
Higashi Nippon Bank	-0.003	(0.011)	-0.005	(0.019)	-0.009	(0.017)	-0.010	(0.009)	0.016	(0.013)	-0.055	(0.045)
Higo Bank	-0.005	(0.009)	-0.018	(0.021)	-0.019	(0.012)	-0.003	(0.013)	-0.002	(0.010)	0.000	(0.022)
Hiroshima Bank	-0.008	(0.007)	-0.040***	(0.014)	-0.022***	(0.003)	-0.008	(0.009)	0.009	(0.011)	0.048**	(0.022)
Hokkoku Bank	-0.013*	(0.007)	-0.038***	(0.014)	-0.018**	(0.007)	-0.014	(0.011)	-0.010	(0.010)	0.000	(0.015)
Hokuetsu Bank	-0.002	(0.009)	-0.008	(0.009)	0.010	(0.006)	0.003	(0.010)	-0.018	(0.012)	0.009	(0.028)
Hokuhoku Finl. Gp.	-0.029	(0.018)	-0.005	(0.034)	-0.033*	(0.017)	-0.021	(0.019)	-0.023	(0.036)	-0.025	(0.058)

Hyakugo Bank	-0.015**	(0.006)	-0.032	(0.019)	-0.020***	(0.006)	-0.017**	(0.007)	-0.006	(0.009)	-0.006	(0.025)
Hyakujushi Bank	-0.012	(0.008)	-0.040	(0.038)	-0.020**	(0.010)	-0.007	(0.007)	-0.005	(0.011)	-0.013	(0.042)
Iyo Bank	-0.009	(0.007)	-0.014	(0.024)	-0.009	(0.010)	-0.012	(0.009)	-0.014	(0.009)	-0.008	(0.012)
Joyo Bank	-0.007	(0.009)	-0.014	(0.015)	-0.003	(0.011)	0.001	(0.014)	-0.010	(0.012)	0.002	(0.031)
Juroku Bank	-0.014	(0.009)	-0.012	(0.026)	-0.017	(0.017)	-0.014	(0.010)	-0.018	(0.011)	-0.006	(0.014)
Kagoshima Bank	-0.011	(0.008)	-0.040***	(0.009)	-0.005	(0.008)	-0.010	(0.009)	-0.007	(0.014)	0.000	(0.025)
Keiyo Bank	-0.006	(0.007)	-0.047***	(0.007)	-0.030***	(0.009)	-0.004	(0.008)	0.014*	(0.008)	0.038***	(0.010)
Miyazaki Bank	-0.021*	(0.011)	-0.076***	(0.029	-0.026*	(0.014)	-0.009	(0.009)	0.001	(0.012)	0.026	(0.018)
Musashino Bank	-0.005	(0.006)	-0.016	(0.015)	-0.008	(0.006)	-0.005	(0.009)	-0.002	(0.007)	0.018**	(0.009)
Nanto Bank	-0.023**	(0.010)	-0.009	(0.025)	-0.017	(0.014)	-0.025***	(0.009)	-0.036	(0.022)	-0.036	(0.024)
Nishi-Nippon City Bank	-0.002	(0.006)	0.011	(0.010)	-0.013*	(0.007)	0.003	(0.007)	0.003	(0.013)	0.017	(0.039)
Ogaki Kyoritsu Bank	-0.013*	(0.007)	-0.028	(0.017)	-0.011	(0.008)	0.001	(0.009)	-0.011	(0.008)	-0.021	(0.019)
Oita Bank	-0.015*	(0.008)	-0.024*	(0.014)	-0.013	(0.009)	-0.012	(0.012)	-0.008	(0.013)	-0.031*	(0.016)
San-In Godo Bank	-0.009	(0.009)	-0.014	(0.016)	-0.009	(0.011)	-0.013	(0.012)	-0.001	(0.018)	0.001	(0.030)
Seventy-seven Bank	-0.012	(0.012)	-0.028	(0.023)	-0.003	(0.019)	-0.007	(0.009)	-0.017	(0.019)	0.001	(0.029)
Shinsei Bank	0.010	(0.019)	-0.029	(0.080)	0.013	(0.027)	-0.002	(0.025)	0.020	(0.025)	0.082	(0.061)
Shizuoka Bank	-0.005	(0.011)	0.001	(0.035)	-0.010	(0.015)	-0.010	(0.013)	-0.004	(0.017)	-0.004	(0.017)
Sumito Mitsui Finl. Gp.	-0.011	(0.009)	-0.019	(0.040)	-0.016	(0.023)	-0.004	(0.014)	-0.011	(0.011)	-0.032	(0.039)
Suruga Bank	-0.011	(0.015)	0.006	(0.036)	0.003	(0.027)	-0.004	(0.024)	-0.036*	(0.020)	-0.039	(0.026)
Tochigi Bank	-0.009	(0.006)	-0.031**	(0.012)	-0.020**	(0.008)	-0.012*	(0.006)	0.002	(0.008)	0.016	(0.012)
Toho Bank	-0.013*	(0.007)	-0.010	(0.022)	-0.023	(0.014)	-0.014	(0.010)	0.000	(0.008)	0.032	(0.034)
Tokoyo Tomin Bank	0.038*	(0.021)	0.132	(0.102)	0.005	(0.041)	0.028	(0.028)	0.057	(0.046)	0.093	(0.108)
Yachiyo Bank	-0.068	(0.064)	-0.019	(0.891)	-0.063	(0.054)	-0.027	(0.040)	-0.010	(0.046)	-0.003	(0.029)
Yamagata Bank	-0.012*	(0.007)	-0.032	(0.026)	-0.011	(0.010)	-0.011	(0.009)	-0.009	(0.009)	-0.012	(0.019)
Yamaguchi Finl.G.	0.018	(0.028)	-0.039	(0.081)	0.012	(0.054)	0.008	(0.037)	0.050	(0.047)	0.055	(0.036)

Note: OLS and QR regression results from Equation (4.6) and examine the relation between trading volume and the stock returns for each bank in our sample. **Standard errors** are displayed in parentheses below the **coefficients**. Asterisks *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Panel B: Changes in prices and lagged-trading volume for individual banks

	OLS		Q05		Q25		Q50		Q75		Q95	
	Volume		**Volume**		**Volume**		**Volume**		**Volume**		**Volume**	
Aichi Bank	-0.007	(0.008)	-0.032*	(0.018)	-0.015	(0.011)	-0.017**	(0.008)	0.010	(0.014)	0.038*	(0.019)
Akita Bank	-0.013	(0.009)	-0.031	(0.029)	-0.016**	(0.008)	-0.014	(0.012)	-0.008	(0.018)	0.010	(0.026)
Aomori Bank	0.002	(0.006)	0.004	(0.020)	-0.002	(0.010)	0.011	(0.009)	0.003	(0.007)	-0.011	(0.012)
Aozora Bank	-0.032	(0.031)	-0.078	(0.170)	-0.130	(0.086)	-0.015	(0.038)	-0.019	(0.029)	0.080	(0.082)
Awa Bank	-0.008	(0.006)	-0.031***	(0.011)	-0.007	(0.008)	-0.003	(0.0078)	-0.013	(0.008)	0.013	(0.025)
Bank Of Iwate	-0.004	(0.008)	0.002	(0.020)	-0.003	(0.017)	-0.002	(0.009)	-0.010	(0.009)	0.001	(0.029)
Bank Of Kyoto	-0.016**	(0.007)	-0.036***	(0.010)	-0.013	(0.008)	-0.007	(0.009)	-0.010	(0.013)	-0.030**	(0.012)
Bank Of Nagoya	-0.009	(0.007)	-0.041*	(0.022)	-0.028***	(0.009)	-0.018**	(0.007)	-0.001	(0.009)	0.033***	(0.013)
Bank Of Okinawa	-0.002	(0.008)	-0.048**	(0.019)	-0.015*	(0.008)	0.003	(0.007)	0.015	(0.011)	0.039	(0.025)
Bank Of The Ryukyus	-0.009	(0.007)	-0.041**	(0.017)	-0.022***	(0.004)	-0.018**	(0.007)	0.009	(0.011)	0.038*	(0.020)
Bank Of Yokohama	-0.010	(0.011)	-0.033	(0.029)	0.001	(0.011)	0.021*	(0.011)	-0.038	(0.024)	-0.020	(0.040)
Chiba Bank	-0.016	(0.015)	-0.012	(0.024)	-0.014	(0.017)	-0.031*	(0.018)	-0.031*	(0.016)	-0.054	(0.059)
Chugoku Bank	-0.008	(0.007)	-0.012	(0.014)	0.000	(0.011)	-0.001	(0.011)	-0.017	(0.013)	-0.020	(0.013)
Daishi Bank	-0.012*	(0.007)	-0.024	(0.018)	-0.017*	(0.008)	-0.013	(0.012)	-0.015	(0.012)	-0.003	(0.013)
Fukui Bank	-0.025**	(0.010)	-0.029	(0.045)	-0.040***	(0.014)	-0.012	(0.014)	-0.018	(0.016)	-0.032*	(0.019)
Fukuoka Financial Gp.	-0.029	(0.026)	0.027	(0.071)	-0.006	(0.037)	-0.046**	(0.023)	-0.066	(0.042)	0.009	(0.137)
Gunma Bank	-0.009	(0.007)	-0.010	(0.017)	-0.008	(0.0058)	-0.004	(0.009)	0.001	(0.012)	-0.016	(0.027)
Hachijuni Bank	-0.014*	(0.008)	-0.030*	(0.017)	-0.017	(0.010)	-0.007	(0.012)	-0.014	(0.010)	-0.042***	(0.016)
Higashi Nippon Bank	-0.004	(0.013)	-0.006	(0.036)	-0.004	(0.020)	-0.012	(0.010)	0.007	(0.016)	-0.058	(0.042)
Higo Bank	-0.005	(0.010)	-0.017	(0.014)	-0.011	(0.013)	-0.009	(0.011)	0.007	(0.016)	-0.015	(0.023)
Hiroshima Bank	-0.012*	(0.006)	-0.041**	(0.018)	-0.023***	(0.004)	-0.013**	(0.007)	0.006	(0.013)	0.009	(0.027)
Hokkoku Bank	-0.010	(0.010)	-0.048**	(0.022)	-0.016	(0.010)	-0.014	(0.013)	-0.004	(0.017)	0.021*	(0.011)
Hokuetsu Bank	0.001	(0.008)	-0.002	(0.010)	0.012	(0.007)	0.003	(0.012)	-0.010	(0.011)	0.007	(0.034)
Hokuhoku Finl. Gp.	-0.028	(0.024)	0.008	(0.033)	-0.013	(0.029)	-0.014	(0.023)	-0.032	(0.033)	-0.121***	(0.042)
Hyakugo Bank	-0.014**	(0.007)	-0.038	(0.025)	-0.019***	(0.006)	-0.019**	(0.009)	-0.012	(0.014)	-0.017	(0.031)
Hyakujushi Bank	-0.011	(0.009)	-0.039*	(0.023)	-0.021**	(0.008)	-0.005	(0.008)	0.000	(0.012)	-0.021	(0.031)

Iyo Bank	-0.009	(0.007)	-0.015**	(0.007)	-0.007	(0.011)	-0.007	(0.012)	-0.006	(0.008)	-0.009	(0.012)
Joyo Bank	-0.006	(0.0010)	-0.014	(0.025)	-0.011	(0.017)	0.003	(0.016)	-0.006	(0.011)	0.002	(0.032)
Juroku Bank	-0.012	(0.010)	-0.017	(0.033)	-0.019	(0.014)	-0.011	(0.014)	-0.007	(0.013)	0.004	(0.013)
Kagoshima Bank	-0.010	(0.008)	-0.0226*	(0.012)	-0.004	(0.009)	-0.012	(0.010)	-0.003	(0.017)	-0.010	(0.028)
Keiyo Bank	-0.007	(0.007)	-0.049***	(0.012)	-0.025**	(0.011)	-0.008	(0.007)	0.009	(0.007)	0.045***	(0.013)
Miyazaki Bank	-0.012	(0.009)	-0.066*	(0.035)	-0.012	(0.014)	-0.003	(0.007)	-0.007	(0.014)	0.021	(0.021)
Musashino Bank	-0.009	(0.006)	-0.013	(0.018)	-0.009*	(0.005)	-0.011	(0.009)	-0.005	(0.008)	0.017	(0.016)
Nanto Bank	-0.001	(0.009)	-0.027	(0.028)	0.015	(0.011)	0.007	(0.008)	0.006	(0.015)	-0.042	(0.030)
Nishi-Nippon City Bank	-0.003	(0.006)	0.012	(0.012)	-0.014	(0.009)	0.000	(0.007)	-0.002	(0.013)	0.018	(0.032)
Ogaki Kyoritsu Bank	-0.014**	(0.007)	-0.022	(0.015)	-0.013*	(0.007)	0.002	(0.013)	-0.018**	(0.008)	-0.012	(0.018)
Oita Bank	-0.011	(0.008)	-0.028*	(0.015)	-0.012	(0.010)	-0.006	(0.014)	-0.003	(0.012)	-0.025	(0.019)
San-In Godo Bank	-0.014	(0.010)	-0.011	(0.018)	-0.019	(0.016)	-0.013	(0.015)	-0.012	(0.014)	0.002	(0.028)
Seventy-seven Bank	-0.012	(0.013)	-0.032	(0.021)	-0.016	(0.024)	-0.007	(0.014)	-0.017	(0.027)	0.002	(0.018)
Shinsei Bank	0.011	(0.024)	0.079	(0.112)	-0.027	(0.030)	-0.023	(0.015)	0.017	(0.032)	0.079	(0.080)
Shizuoka Bank	-0.007	(0.011)	-0.006	(0.014)	-0.010	(0.017)	-0.006	(0.015)	-0.002	(0.013)	-0.017	(0.022)
Sumito Mitsui Finl. Gp.	-0.005	(0.020)	0.014	(0.051)	-0.025	(0.028)	-0.004	(0.016)	-0.008	(0.023)	-0.028	(0.045)
Suruga Bank	-0.013	(0.016)	0.012	(0.027)	0.010	(0.022)	-0.004	(0.023)	-0.049**	(0.022)	-0.048	(0.030)
Tochigi Bank	-0.011*	(0.006)	-0.031***	(0.010)	-0.019***	(0.005)	-0.014*	(0.008)	0.004	(0.009)	0.008	(0.016)
Toho Bank	-0.013*	(0.007)	-0.014	(0.021)	-0.024	(0.015)	0.007	(0.011)	-0.001	(0.009)	-0.029	(0.031)
Tokoyo Tomin Bank	0.030	(0.033)	-0.028	(0.112)	0.012	(0.080)	0.015	(0.060)	0.063	(0.081)	0.108	(0.102)
Yachiyo Bank	-0.024	(0.024)	-0.015	(0.061)	-0.054*	(0.032)	-0.038	(0.037)	0.021	(0.048)	-0.002	(0.033)
Yamagata Bank	-0.007	(0.008)	-0.043**	(0.020)	-0.002	(0.010)	-0.002	(0.009)	-0.003	(0.012)	-0.005	(0.016)
Yamaguchi Finl.G.	0.027	(0.025)	-0.002	(0.083)	0.051	(0.039)	0.015	(0.035)	0.015	(0.045)	0.045	(0.051)